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

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Abstract

We show that firms increase their pollution intensity as they become more financially distressed. This is particularly the case in high-environmental liability risk locations, akin to a risk-taking motive. We rationalize these facts by calibrating a dynamic model featuring endogenous default, and dirty vs. clean investment. Dirty assets reduce short-term costs but expose firms to persistent liability and regulatory risks. Thus, as firms become more financially distressed, they gradually take on more risk and shift the composition of their assets toward the more polluting ones. Our counterfactuals highlight the limited environmental impact of blanket divestments when heightened financing costs lead firms to increase their pollution intensity while scaling down. Tilting strategies, however, are more effective at tapering pollution.

JEL Classification: G30; G33; G38; O44; Q50.

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1 Introduction

How do financial conditions affect corporate pollution? A popular narrative posits that increased financing costs stemming from divestment campaigns can lead firms to scale down their investments and operations. As a result, firms reduce their size and thus pollution through the extensive margin. This argument, however, abstracts from the fact that such increased financing costs can also lead to heightened financial distress. Insofar as polluting assets reduce short-term costs and expose firms to environmental liability risks, firms may shift the composition of their assets toward the more polluting ones as they approach default (Jensen and Meckling, 1976; Shavell, 1986). This pollution-shifting mechanism operates along the *intensive* margin, increasing pollution intensity, which we define as pollution per asset. While financing costs may impact the intensive and extensive margins of pollution in opposite ways, the literature provides little guidance to evaluate both empirically and quantitatively their joint effects. The objective of this paper is to accomplish that step.

Disentangling the extensive and intensive margins of pollution is difficult to perform empirically.[1] We use a unique high-frequency project-level dataset from the oil and gas industry and three different empirical strategies to show that firms with higher financing costs are more likely to increase pollution in the intensive margin. The relationship between financing costs and pollution intensity is mostly held in locations with high environmental liability risks. We also document that these firms simultaneously reduce investment, thus diminishing pollution on the extensive margin.

We then calibrate a rich dynamic corporate finance model with endogenous leverage, default, clean vs. dirty asset choice, and financing frictions to rationalize these empirical facts, decompose the extensive and intensive margins of pollution, and study the implications of several forms of divestment approaches and regulatory settings. Our core modeling assumption resides in the following distinction: dirty assets have lower operating costs but increase a firm's exposure to liability risks related to environmental fines, lawsuits, and future regulations. These costs are less likely to matter for financially distressed firms, when their shareholders are not subject to these liabilities in bankruptcy. As a result, financially distressed firms may have further incentives to shift the composition of their assets toward the more polluting ones, akin to a risk-taking motive. Our counterfactuals give three main conclusions.

[1] Firms can adjust their product mix and decide whether to produce goods in-house or source them from external suppliers (Duchin, Gao, and Xu, 2025). They can also change the product they sell. All these decisions, which affect a firm's pollution, are difficult to observe.

First, divestment policies aimed at increasing uniformly financing costs of polluting sectors may prove to be modest or even counterproductive if the pollution-shifting effect (intensive margin) offsets the decrease in size (extensive margin). Second, the relationship between financing costs and pollution critically depends on a firm's capital structure. Third, strategies contingent on pollution intensity, such as debt tilting, can, in fact, reduce pollution intensity and be more effective.

We now turn to the details of our analysis. We assemble a high-frequency database of U.S.-located oil and gas projects completed between 2012 and 2022. We then develop two measures, namely: (i) a measure of gas flaring relying on recent advances in satellite imaging and remote sensing, and (ii) a measure of toxic releases, based on an administrative database. Together these two measures provide a 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 across projects (Gilje and Taillard (2015), Gilje, Loutskina, and Murphy (2020). We also exploit the high frequency of our dataset to run monthly-level event studies.

The fossil fuel industry provides a relevant setting for our research objective for multiple reasons. First, it is responsible for significant air and water pollution, as oil and gas operations contribute approximately 15% of global energy-related greenhouse gas emissions (International Energy Agency, 2023). Second, the capital structure of oil and gas companies involves high 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. Such divestment has been recently encouraged through voluntary initiatives and regulatory proposals considering implementing green capital requirements or green repo (Bolton et al. (2020), Oehmke and Opp (2021)).

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, and 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. As a result, 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.

Next, we proceed to develop and calibrate a rich dynamic model to rationalize our empirical results and provide further intuition as to the underlying economic mechanism and the feedback between financial distress and the pollution intensity of investments. We augment a standard discrete-time dynamic model of capital structure with endogenous leverage, default, 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.[2] 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 cash flow 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. Further, these pollution decisions may have long-lasting effects when such investments are only partially reversible.

[2] 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.

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 highlighting the distinct effects associated with the extensive (i.e., firm size) and intensive (i.e., clean vs. dirty asset composition) margins of pollution in our quantitative analysis. We find that the relationship between financing costs and pollution critically depends on a firm's capital structure, financial health, and corresponding elasticities of both margins.

We start by investigating the implications of uniform equity or debt issuance cost increases, which we interpret as a direct objective of blanket divestment policies. We find that the effects of higher issuance costs appear to be ambiguous and critically depend on their magnitude. In particular, they appear to be either counterproductive or modest at best for a wide range of values, but ultimately become more significant when they are very large.

The reason behind such ambiguous impact resides in the presence of two countervailing forces stemming from the intensive and extensive margins, respectively. Indeed, an increase in issuance costs hampers financing flexibility and has a negative effect on cash flows and investments. As taking on additional leverage becomes more costly, firms experience a reduction in net earnings and/or lower their growth rate. Thus, the ensuing decline in firm size and financial flexibility combined with adverse productivity shocks lead to heightened distress, further amplifying credit spreads. Ultimately, whether these changes lead to more or less firm-level pollution depends on the relative elasticities of each margin and the frequency and relevance of debt or equity financing. Taking the argument to the extreme, when debt issuance costs are exorbitantly high, leverage becomes negligible and so as the pollution-shifting motives. As a result, firm pollution declines with size as the intensive margin effect vanishes.

Our analyses also investigate the effects of policies that depend on pollution intensity and provide further financial incentives for firms that favor clean assets. Such incentives can, for example, be derived from: (i) debt cost tilting (i.e., debt issuance costs increase with pollution intensity), or (ii) asset cost tilting (i.e., divestment costs increase with or recovery value upon default decrease with pollution intensity). Tilted debt issuance costs exemplify investors' heightened preferences for green firms or green debt, in addition to contractual arrangements such as sustainability-linked debt, which directly tie a firm's cost of credit to its sustainability performance. Tilted asset costs refer to the lower resale value of dirty assets and relate to potential regulatory burdens or operator preferences that render these assets costly to purchase or use. These costs negatively affect firm cash flows, either because it is more expensive to sell dirty assets, or because credit spreads increase due to their lower recovery value.

Our counterfactual exercises point to the fact that policies with such built-in incentives can endogenously urge firms to lower their pollution intensity. As a result, they potentially reduce credit risk and counteracting the asset substitution motive and can be more effective at tapering pollution. For example, through the lens of our calibrated model, we find that a debt issuance costs that is three times higher for a 100% dirty firm relative to a 100% clean firm (i.e., an increase in costs of about 1.3%) can lead to a decline in firm-level pollution by over 40%.

Overall, our quantitative analysis highlights that, one may tend to overestimate significantly the effects of increased financing costs, absent any consideration for the intensive margin channel. As a result, it raises doubt as to the relevance of blanket divestment campaigns and points 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 can prove more effective.

Related Literature. Our work revolves around research strands on (i) corporate environmental decisions and financial frictions, (ii) asset substitution theory, and (iii) dynamic capital structure models.

We contribute 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, our empirical setting allows us to distinguish the intensive and extensive margins of pollution, and we explore a complementary yet distinct channel associated with financial distress and risk-taking. Further, a notable feature of our work resides in providing theoretical foundations and calibrating a model to investigate quantitatively the effects of different sustainability investment policies.

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 how the riskiness of polluting assets – as opposed to their fixed setup costs – affects investment decisions, and the pollution-shifting motive stemming from financial distress. Further, we allow for endogenous size, capital structure, and default, the feedback between pollution intensity choices and financing costs, and debt and equity financing frictions. All these distinct features are critical to investigating 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 (2025), Zerbib (2022), 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, our analysis is complementary to recent work by Hartzmark and Shue (2023) who exploit cross-industries variations to show that an increase in the cost of capital can lead to a further increase in pollution for high-pollution firms. 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, the distinct effects of equity and debt divestments, and alternative policies such as debt tilting. Our quantitative analysis also enables us to show how a firm's pollution is ultimately affected by interest rates, credit risk, and changes in debt and equity issuance costs.[3]

Our work 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. He classifies exploratory projects as risky and development ones as safe and shows that firms

[3]Relatedly, we also contribute to the literature on how environmental government policies interact with environmental private initiatives (Bensoussan et al., 2022; Biais and Landier, 2022; Huang and Kopytov, 2023; Allen, Barbalau, and Zeni, 2023; Döttling and Rola-Janicka, 2023; Pedersen, 2023; Piatti, Shapiro, and Wang, 2023; Carlson, Fisher, and Lazrak, 2022). Our paper suggests that the uncertainty surrounding future environmental regulation can diminish the efficiency of investors' divestment campaigns.

with more covenants, shorter debt maturity, and more bank debt are more likely to increase their safer projects, consistent with the effectiveness of bank monitoring in reducing risk-shifting. 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 quantitative 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, an asset substitution motive, and our focus on investigating quantitatively how capital structure and financial distress affect pollution choices.[5] Our setting differs in that firms choose the clean or dirty nature of their investments. In light of the partial irreversibility of such investment, the exposure to environmental risks cannot be promptly adjusted. Further, creditors rationally anticipate asset substitution incentives and adjust the price of corporate debt ex-ante, mitigating excessive risk-taking.

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

2 Data

2.1 Measures of Pollution

The oil and gas extraction process creates an important number of environmental externalities. Our paper accounts for two complementary and granular measures of pollution, constructed at the well-level, namely: (i) flaring, and (ii) the use of toxic chemicals in the fracturing process.

[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), accounting for the level of risk of the firm's cash flow process.

It is important to highlight the unique characteristics of our measures and how they allow us to distinguish between the extensive and intensive margins of pollution in a relatively more refined way compared to other existing approaches. For example, a common approach to measuring pollution intensity is to consider firm-level or establishment-level pollution data provided by Toxics Release Inventory (TRI) or Trucost, normalized by a proxy for sales or production. However, this approach comes with a major drawback: the econometrician could observe a spurious reduction in pollution intensity if a firm alters its product mix or outsources inputs that were previously produced in-house. These issues are less pronounced in our empirical context, as we observe the specific type of output, namely, oil or gas. Moreover, our well-level dataset enables us to link directly pollution to the actual output, thereby providing a more accurate measure of pollution intensity.

2.1.1 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 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.[6]

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

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.[7] 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.[8] 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 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.[9]

We use the local temperature of the hot point to identify flaring, which emits a temperature between 950°C and 2250°C. This temperature range is distinct from that of 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 consistent with flaring within a 750-meter radius around the location of a given well. We then count total flaring detections between days 1 and 90 of production. One notable limitation is that it is possible that multiple wells can be in close proximity to each other. In this case, we may not be able to disentangle the exact flaring

[7] 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

[8] 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.

[9] 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.

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, 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 7 in the online appendix 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.[10]

2.1.2 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 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).

2.2 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

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

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.

2.3 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.

2.4 Sample and Descriptive Statistics

We start with the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We use this dataset to provide broad descriptive statistics regarding firms' leverage, investment, and cash flow dynamics.

We then use a dataset where we observe pollution decisions for both private and public firms, as well as whether the firm has filed for bankruptcy. This dataset is only available after 2012. We use this dataset separately for our bankruptcy tests. We match this dataset with pollution information available at the well level to the sample of Compustat firms. We have 78 unique firms that drilled a U.S. onshore well between 2012 and 2022, giving us 78,044 unique projects.

Finally, we use a project-level dataset with information on production. To make this sample comparable with the pollution measures, we restrict the sample period to post-2012. This sample 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.

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. Firms in our sample are, on average, highly leveraged. Namely, an oil and gas project comes from a firm with an average market 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.

3 Empirical Results

In this section, we explore two margins through which financial factors can affect a firm's pollution intensity, 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).

3.1 Financially Distressed Firms Pollute More in the Intensive Margin

We first plot the binscatters of the relationship between pollution intensity and proxies for financial distress. Plotting the relationship in a graph ensures that the relationship is monotonic and not driven by abnormal observations. Panel A of Figure 1 shows the relationship between pollution intensity and the Altman Z-score, while Panel B of Figure 1 uses firm leverage. In both graphs, we can observe the same fact: financial distress is positively related to pollution intensity. Moreover, the relationship becomes more precise and stronger once we control for the size of the company or location fixed effects.

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 intensity 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 and 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 (Gilje, Loutskina, and Murphy, 2020).

Next, we show that the positive relationship between pollution intensity 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. Fist, we investigate the evolution of pollution intensity 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 intensity following a Chapter 11 filing.

We empirically test this prediction. Figure 2 plots the average difference in the probability of polluting, in the intensive margin, 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, in the intensive margin, 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 intensity. Our results are also consistent with Ohlrogge (2023) who examines industrial water contamination and finds that firms reduce their pollution after Chapter 11 filing.

The second set of tests exploits the fact that we have precise timestamps for each project, which allows us to run high-frequency event studies. We derive firm-level one-year default probabilities, relying on an annual rolling logit regression approach and accounting for both balance sheet and market variables, as described in Boualam, Gomes, and Ward (2020). We denote this default probability measure, $\text{Lprob}_{i,t+j}$, for firm i and month $t+j$, and construct it on a monthly basis across all publicly-listed firms in our sample. We then estimate the following equation for a given project k, made by firm i at time t and for $j = -6, -5, ..., 5, 6$:

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

where Pollution is a dummy variable that takes the value of one if the well pollutes and zero otherwise. Notice that this dummy variable captures pollution in the intensive margin, that is, the pollution conditional on total production. Controls_{ikt} is a set of firm and project characteristics namely firm size, sales, Capex, Tobin's Q, total liabilities, return on asset, and the first 6 month of oil and gas production. FE_{ikt} contains a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect.

Figure 3 plots the coefficients, where j goes from -6 to 6. The main insight is that the relationship between default probability and pollution intensity has an inverted U-shape that peaks one month before the well completion. Specifically, the impact of distress risk is relatively low for $j = -6$, gradually increases until one month before completion, and then declines afterwards. This event study confirms the view that a firm's financial health and distress level are key behind its pollution decision.

We then decompose the previous dynamic event study graph on two subsamples, to show that the relationship between pollution intensity and distress is stronger when potential liabilities associated with pollution are stronger. We use the Lawsuit Climate Survey to obtain variations in environmental liability risks. This survey reports corporate perceptions about the fairness and reasonableness of state liability systems, and thus reflects firms' subjective ex-ante expectations about potential costs faced within a given state.

Figure 4 exhibits the impact of the probability of default on pollution intensity for projects located in states with high (in red) and low (in grey) perceived liability risks, respectively. Clearly, this relationship is almost 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 intensity should be stronger when potential environmental liabilities are stronger.

3.2 Financially Distressed Firms Produce Less

In this subsection, we show that a higher probability of default is also 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.[11]

We plot the binscatter of the average number of projects per year for each firm as a function of proxies for financial distress. Figure 8 in the online appendix reports the results for Altman's Z-score while Figure 9 in the online appendix, report those for leverage. For both figures, we plot the raw relationship on the left, and the binscatter with controls such as firm size on the right. Overall, we show a clear negative relationship between the number of projects started and these two measures. Table 8 provides the estimates in a regression framework, where the dependent variable is the firm's number of new projects in a given year and basin.

Column (1) shows that financially-distressed firm (i.e., with an Altman Z-score below 1.8) reduce the number of their 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

[11] In the context of the oil and gas industry, 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.

omitted variables, such as differences in investment opportunities that vary with financial distress. They are also likely to be "contaminated controls", because they 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.

4 A Dynamic Model of Financial Distress and Pollution Intensity

We extend dynamic 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 pollution intensity through the firm's choice between dirty or clean capital. The distinction between dirty and clean capital resides in the following: on the one hand, clean capital is subject to permanent maintenance costs; on the other hand, dirty capital does not incur any costs unless a stochastic environmental liability shock is realized. In this context, pollution intensity is a dynamic *and* persistent state variable – since investments are only partially reversible – that 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 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 (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 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, are heterogeneous across the following dimensions: capital, k, pollution intensity, 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:

$$\begin{aligned} g(k,k') &= c\left(\frac{k'-(1-\delta)k}{k}\right)^2 k & (3)\\ c &= c_0 \mathbb{1}_{\{k'-(1-\delta)k>0\}} + c_1 \mathbb{1}_{\{k'-(1-\delta)k<0\}}, & (4) \end{aligned}$$

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 the endogenous 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 perfectly substitutable from a production perspective: they require the same investment cost, are subject to the same depreciation rate, and provide the same per-period output. 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:

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

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 $\eta\tau_C k$ 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, and define the corresponding risk-free rate as $r = \frac{1}{\beta} - 1$. 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.

4.5 Equity Value and the Firm Optimization Problem

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

$$e(k,\eta,b,s,\tau_C) = \Pi(k,\eta,b,s,\tau_C) - \left[k' - (1-\delta)k\right] - g(k,k') - b + (1-\lambda_b)qb' + \tau(\delta k + rb). \tag{8}$$

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

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

[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.

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 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 capital investment, i, is exclusively clean (η_i=0) or dirty ($\eta_i = 1$) within a given period , and specify the dynamics of capital and its composition as follows:

$$k' = (1-\delta)k + i \tag{11}$$

$$\eta' = \eta + \frac{(\eta_i - \eta)i}{(1-\delta)k+i}. \tag{12}$$

We note that in the complete absence of pollution liabilities (i.e., $p = 0$), 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, Firm Entry, and Equilbrium

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:

$F_t =$	$\int d\mu_t$	Mass of firms
$K_t =$	$\int k d\mu_t$	Aggregate capital

$$
\begin{array}{rll}
I_t = & \int i d\mu_t & \text{Aggregate investment} \\
B_t = & \int b d\mu_t & \text{Aggregate debt} \\
P_t = & \int k\eta d\mu_t & \text{Aggregate pollution} \\
\Upsilon_t = & \frac{\int k\eta \, d\mu_t}{\int k \, d\mu_t} & \text{Aggregate pollution intensity}
\end{array}
$$

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.

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 a function of both entrants and incumbent firms. At each period, a mass of firm default and exit the economy and are replaced by new entrants characterized by their initial size, debt ,and pollution intensity. Conversely, incumbent firms evolve according to the realization of their idiosyncratic productivity shocks over the next period and their optimal policy functions.

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.[13] Second, we simulate the model-implied moments and minimize the distance with their empirical counterparts. Table 3 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, r, 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,

[13] 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 update both the value function and the price of debt through the iteration procedure. The model solution relies on a discretization of the idiosyncratic shock process following Tauchen and Hussey (1991) and allowing for 7 states.

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 that the model-implied moments, determined based on a panel consisting of 5,000 firms simulated over 30 years, are in line 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 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 auto-

[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 $i = \frac{86}{575} = 15.0\%$.

regressive 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 5 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 the pollution intensity distribution. We note that when productivity is sufficiently high, high-pollution firms tend to be larger than low-pollution firms. The intuition is straightforward. Absent any costly pollution liability, all else equal, high-pollution firms economize the clean asset operating costs, generate higher profits, and scale up faster. However, adverse productivity shocks lead to the opposite behavior. High-pollution firms are more exposed to financial distress and credit risk, which renders their 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 exacerbates firm default probability and credit spreads.

This result is in line with a risk-taking motive, driven by equityholders' limited liability and the firm's 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 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 steady-state firm distribution from the model and compare them to their empirical counterparts.

Pollution sensitivity to default rates, size, leverage, and productivity. Figure 11 in the online appendix 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.

In contrast, the relationship between default probability and pollution intensity exhibits a U-shape pattern. Indeed, firms with no imminent default risk can initially take on more polluting assets, as long as their expected user costs are equal to or cheaper than clean assets. In fact, as probability of default starts to increase, firms may be inclined to hedge themselves again further negative pollution shocks and become greener under certain conditions. However, as firms become severely distressed, their equityholders become more incentivized to take on more risk and thus gradually operate more polluting assets as they gamble for resurrection.

Figure 12 in the online appendix 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, this figure also highlights that average firm pollution also increases 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.

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

Cross-sectional moments. We investigate the model performance in the cross-section. Table 4 reports the cross-sectional averages for both model-implied and empirical moments. These moments further provide additional 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 5 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 that note that equity issuance costs 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 (2025) 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.

Next we move on to debt issuances which represent a 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 extensive (-3.4%) and intensive (+4.1%) margin effects. 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

[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.

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 6 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.

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.

5.4 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.

5.4.1 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 6 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%.

5.4.2 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.

5.4.3 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]

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 intensity measure and proxies for financial distress, such as size, leverage, and Altman Z-score. Second, we investigate how such polluting intensity 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 intensity. We show that the relationship between pollution intensity and default probability is the strongest for concomitant or one-month lag default probabilities. We then show that the relationship between financial distress and pollution intensity is stronger for projects located in high-liability locations.

[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.

Informed by these stylized facts, we develop and calibrate a dynamic endogenous default model with clean and dirty types of capital to study how changes in financial conditions affect 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 but exposes firms to a stochastic pollution liability shock. Firms have incentives to shift toward the more polluting assets as they approach default, akin to a risk-taking motive. Intuitively, pollution liability is not paid upon bankruptcy, which truncates the ex-ante expected cost of polluting.

We use the model to run several counterfactual exercises and discuss the implications for sustainability investment mandates. An increase in the cost of capital, which is the objective of blanket divestment campaigns, has little impact on overall pollution, as firms pollute more in the *intensive* margin, offsetting any reduction in pollution coming from the *extensive* margin. We also document that changes in debt and equity issuance costs may have different effects on total pollution, as they affect the equilibrium leverage differently and, thus, the ex-ante incentives of pollution risk-shifting. Moreover, we show that increases in financing costs for the most polluting firms, which is the objective of tilting strategies, lead to a strong decrease in pollution through the *intensive* margin. Finally, an increase in firms' adjustment costs for polluting capital, one potential unintended consequence of the real divestment of polluted assets, leads to lower ex-ante pollution.

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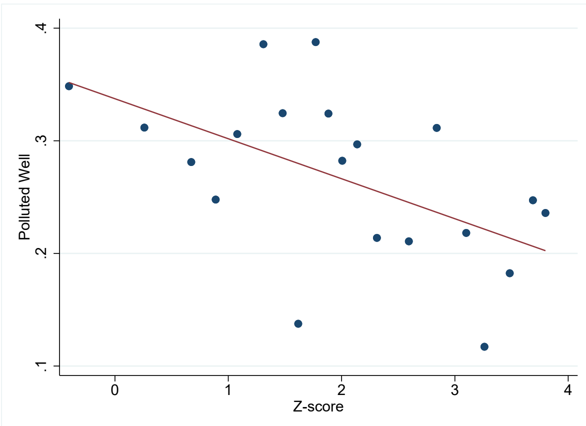
Appendix – Tables / Figures

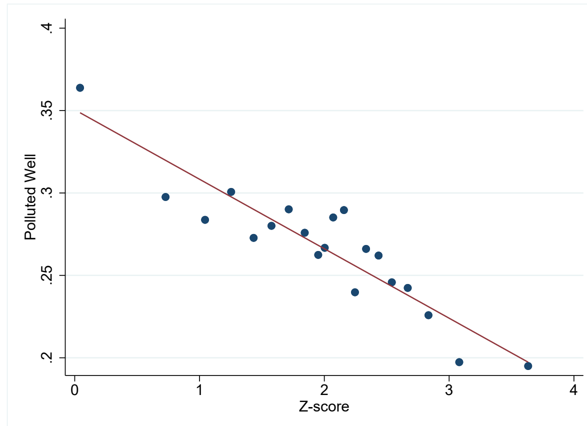
Figure 1: Relationship between Pollution, Leverage, and Financial Distress

Panel A: Pollution and Financial Distress

Without controls

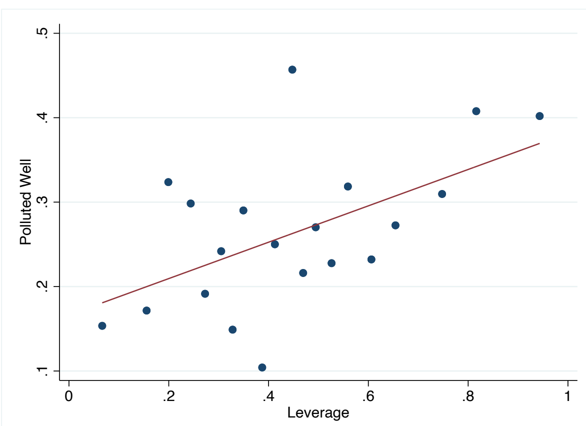


With controls

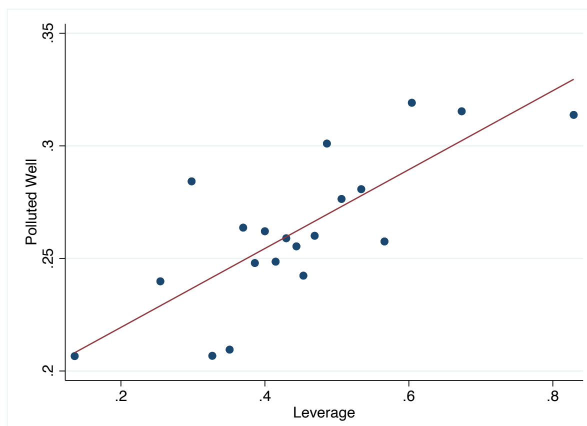


Panel B: Pollution and Leverage

Without controls

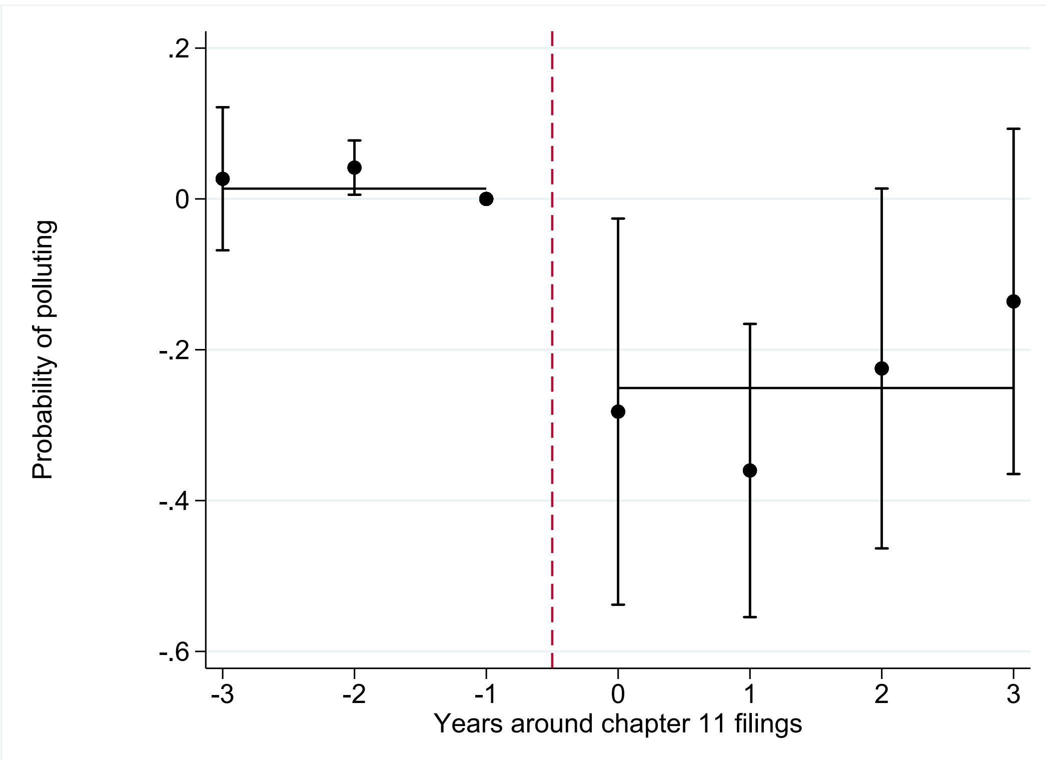


With controls



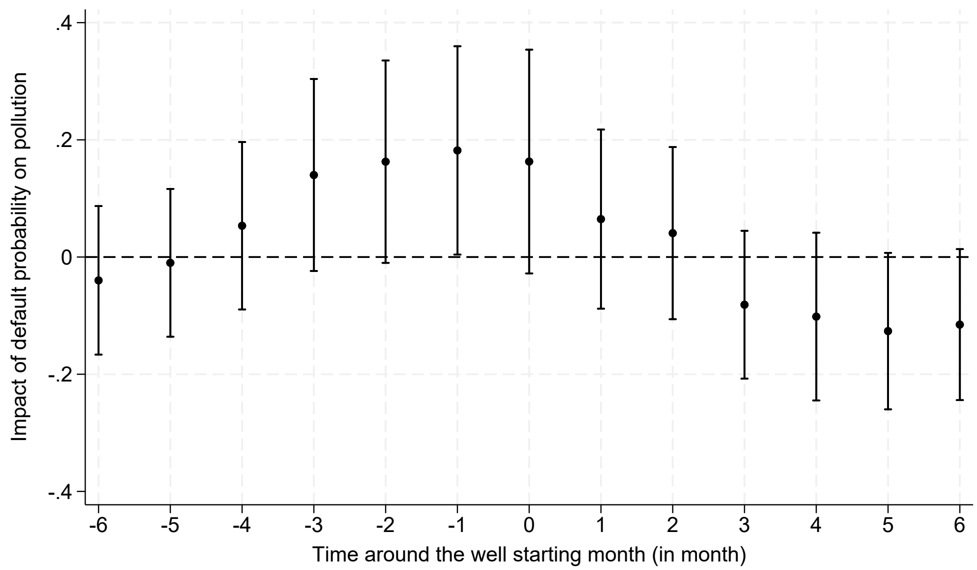
Panel A reports the binned scatterplots of our pollution measure with the Altman z-score. Panel B reports the binned scatterplots between pollution and the firm's leverage The graphs on the left show the relationship without any controls. The graphs on the right show the relationship after the inclusion of a control for the size of the company and a location fixed effect. Pollution is defined as a dummy variable that takes the value of one if the well is either flaring or using toxic chemicals and zero otherwise. Both graphs of Panel A show a negative relationship between pollution and the Z-score, consistent with the idea that firms that are more financially distressed are likely to pollute more. Both graphs of panel B show a positive relationship between leverage and pollution, consistent with the idea that firms that are more financially distressed are likely to pollute more. For panel B, we exclude outliers, i.e., firms for which the leverage is below zero or above one, and show in the econometric regressions that the relationship still holds in the full sample.

Figure 2: Dynamic Graph: Bankruptcy



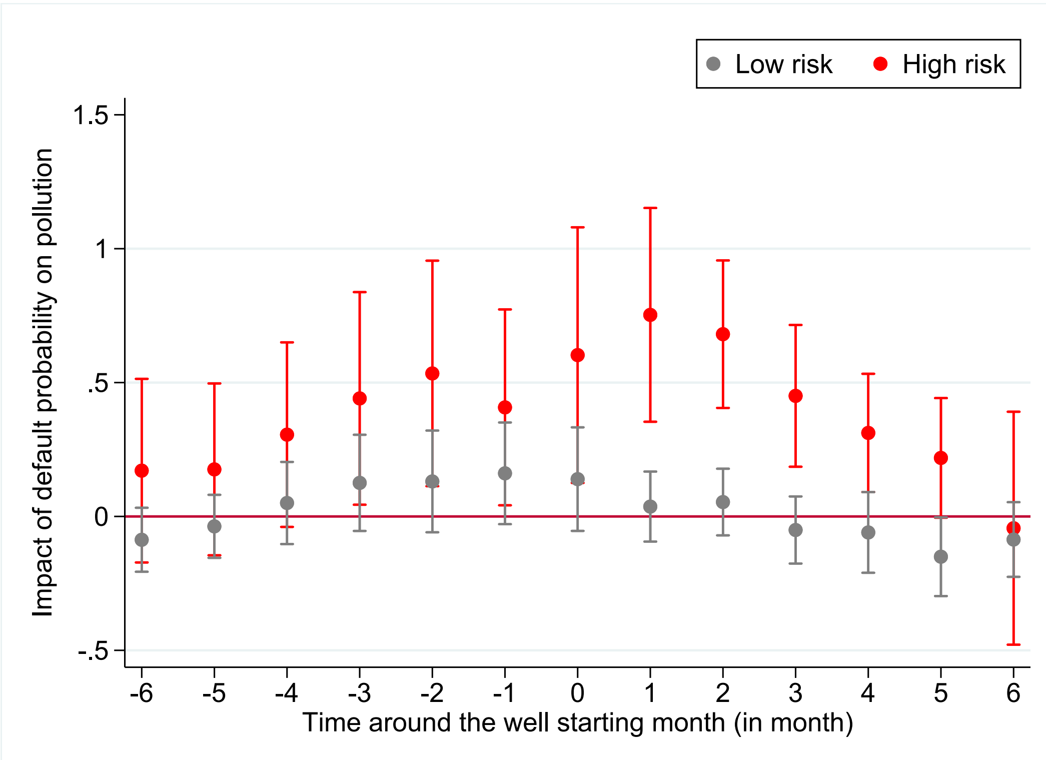
This graph studies the pollution practices before and after a firm files for Chapter 11. The x-axis corresponds to the years around Chapter 11 filing, while the y-axis represents the pollution probability at a given year. This probability is estimated using a dynamic event window in a difference-in-differences regression framework within the sample of firms that file for bankruptcy. Firm, location, and year fixed effects are included.

Figure 3: Dynamic Graph: Around the Well Completion



This graph studies the pollution practices at the monthly frequency, for different lagged probabilities of default. We derive firm-level monthly one-year default probabilities, relying on an annual rolling logit regression approach and accounting for both balance sheet and market variables, as described in Boualam, Gomes, and Ward (2020). We then regress our pollution measure at time t on the probability of default at time $t+j$, where j goes from -6 to 6. We add a set of controls to the regression, including firm characteristics (namely, size, sales, Capex, Tobin's Q, total liabilities, return on asset, and the first 6 month of oil and gas production), a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect. We report the coefficients (y-axis) measuring the relationship between pollution and default probability at time $t+j$, where j goes from -6 to 6 (x-axis).

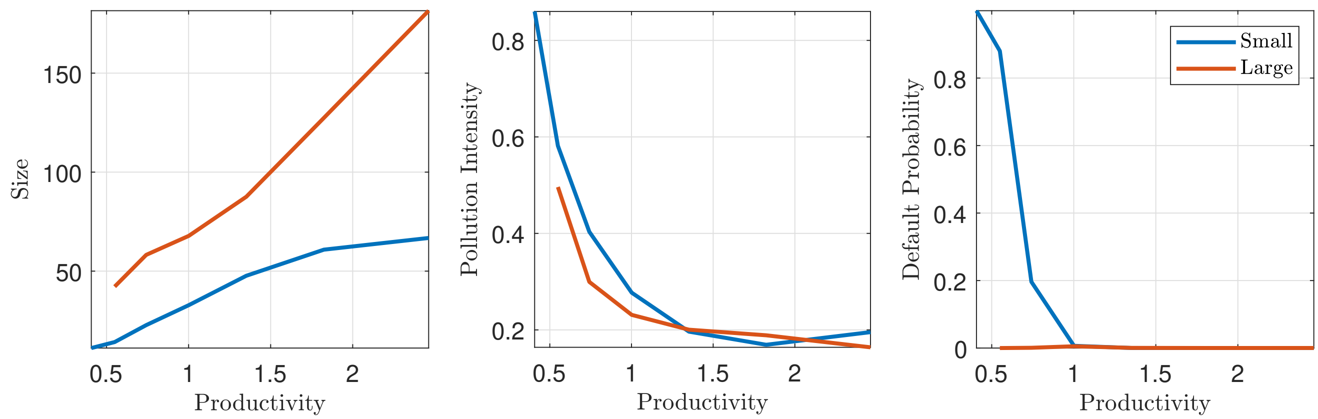
Figure 4: Dynamic Graph: Around the Well Completion: Low vs. High Liability Risk



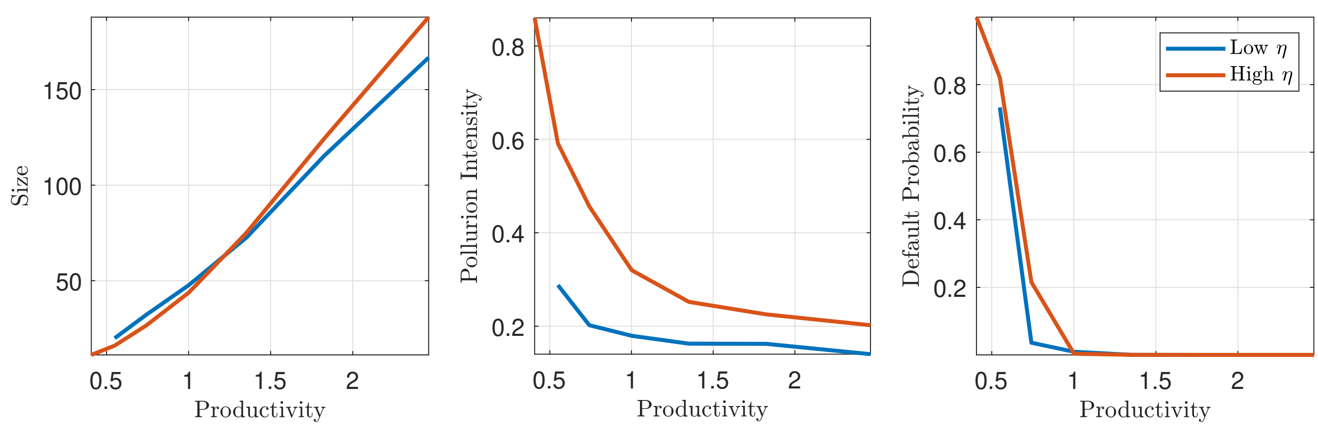
This graph studies the pollution practices at the monthly frequency, for different lagged probability of default. The relationship is estimated on different subsamples: (i) the sample where the perceived liability risk of the location is above the sample median (in red), and (ii) the sample where the perceived liability risk is below the sample median (in gray). We derive firm-level monthly one-year default probabilities, relying on an annual rolling logit regression approach and accounting for both balance sheet and market variables, as described in Boualam, Gomes, and Ward (2020). We then regress our pollution measure at time t on the probability of default at time $t+j$, where j goes from -6 to 6. We add a set of controls to the regression, including firm characteristics (namely, size, sales, Capex, Tobin's Q, total liabilities, return on asset, and the first 6 month of oil and gas production), a firm fixed effect, a location fixed effect, a basin-year fixed effect, and a month fixed effect. We report the coefficients (y-axis) measuring the relationship between pollution and default probability at time $t+j$, where j goes from -6 to 6 (x-axis).

Figure 5: Optimal Policies for Size, Pollution Intensity, and Default Probability

A. Small vs. Large Firms

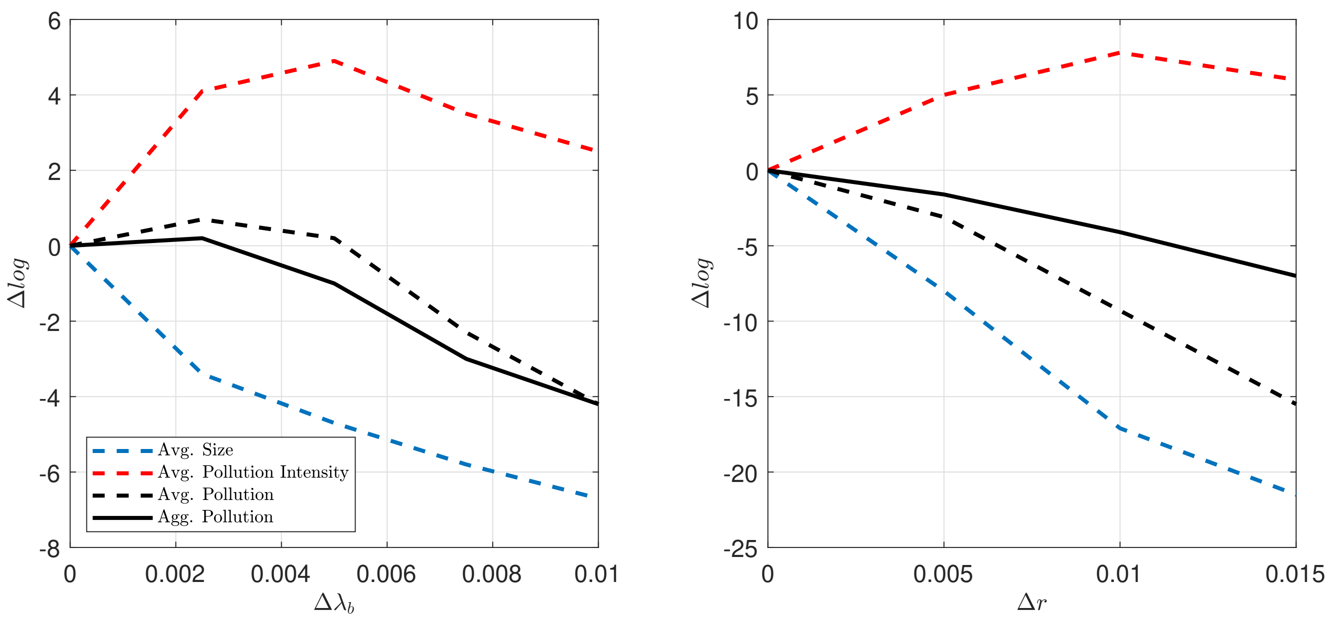


B. Low vs. High Pollution Intensity Firms



This figure plots (i) optimal next-period size, (ii) optimal next-period pollution intensity, and (iii) 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 3.

Figure 6: 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 3. 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. Panel A reports the descriptive statistics based on the sample of public corporations 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. *Pollution* is a dummy variable that takes the value one if the well is flared or using toxic chemicals, and zero otherwise. *First 6 oil* is the first six months of oil in BOE equivalent. *First 6 gas* is the first six months of gas in BOE equivalent. The unit of all the accounting variables is 1000. *Assets - Total* comes from the Compustat variable at. *CAPEX* comes from the Compustat variable capx. *Leverage* is equal to (Long-term debt (dltt) + Debt in Current Liabilities (dlc)) / Stockholders Equity (seq). The Z-score is constructed using the formula displayed in WRDS. Distress is a dummy variable that takes the value one if the Z-score is below 1.8 and zero otherwise. *Cost of capital* is equal to the total of Interest and related expenses (xint) / (Long-term Debt (dltt) + Debt in Current Liabilities (dlc)).

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 uses Altman's Z-score while Panel B uses log-leverage, as proxies 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 one if the well is flared with high intensity and zero otherwise. Number of toxic chemicals$_{it} > 0$ is a dummy variable that takes the value one 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: Parameter Values

Parameter	Value	Description	Target	Data	Model
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					
$\bar{s}$	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_b	0.0025	Debt issuance cost	Avg. Leverage	0.29	0.70
λ_e	0.015	Equity issuance cost	Equity issuance frequency	0.25	0.19
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 4: Cross-Sectional Moments

Asset	Size		Investment		Poll. Intensity	
%tile	Data	Model	Data	Model	Data	Model
0%-25%	32.63	37.2	0.15	0.10	0.39	0.35
25%-50%	202.135	56.3	0.19	0.12	0.31	0.27
50%-75%	1,130.84	77.7	0.21	0.12	0.30	0.26
75%-100%	6,888.63	115.1	0.17	0.11	0.29	0.23

This table reports the cross-sectional moments. The parameter values are reported in Table 3. 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 5: Long-run Effects of Interest Rates, Issuance Costs, and Regulatory Costs

	Size	Debt	Leverage	Default rate	Poll. intensity	Avg. poll.	Agg. poll.
Benchmark	46.73	11.64	0.50	0.05	0.29	11.32	5.7 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 3. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Table 6: Long-run Effects of Alternative Policies: Tilting and Liquidation Values

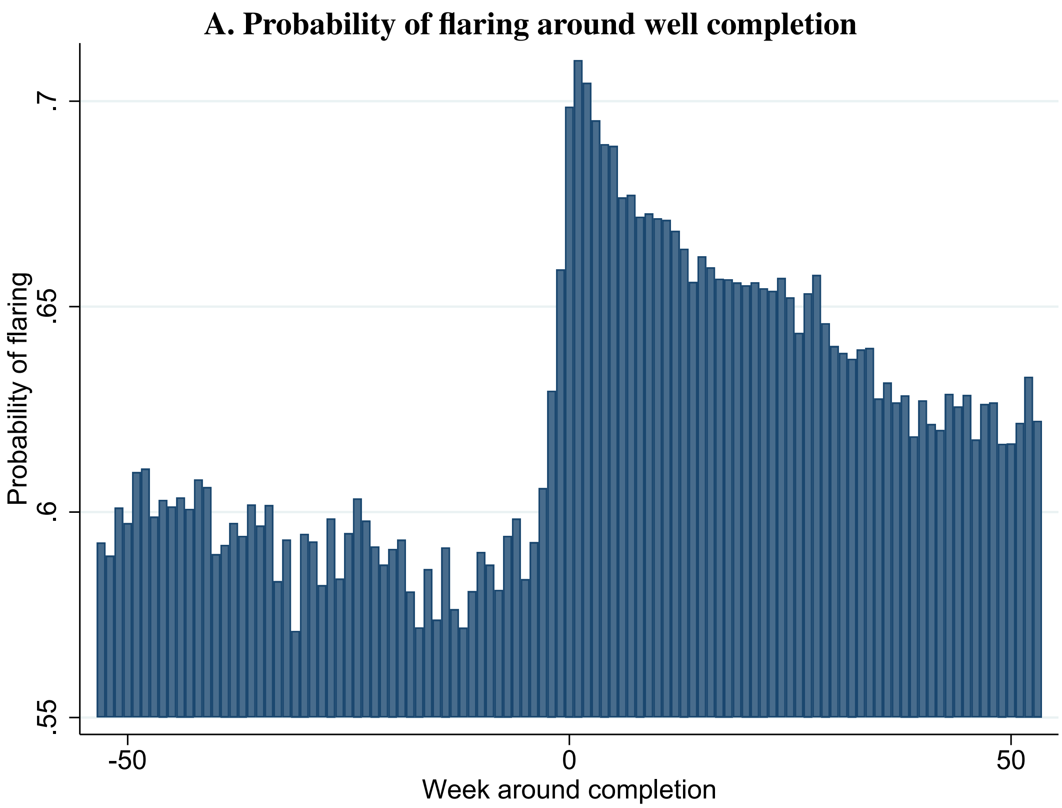
	Size	Debt	Leverage	Default rate	Poll. intensity	Avg. poll.	Agg. poll
Benchmark	46.73	11.64	0.50	0.05	0.29	11.32	$5.7\ 10^4$
A. Uniform Debt Issuance Costs							
$\Delta\lambda_b = 0.0075$	-5.8%	-265.8%	-253.7%	2.8%	3.5%	-2.3%	-3.0%
B. Tilted Debt Issuance Costs							
$\tilde{\lambda}_b$	-3.2%	-7.7%	-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 3, 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 – Not For Publication

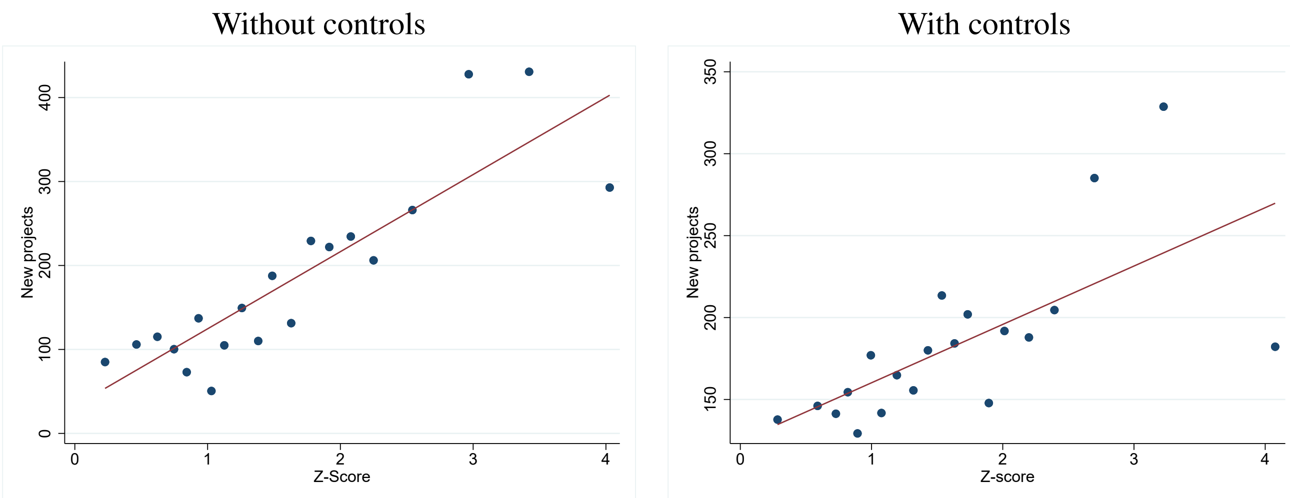
Bellon-Boualam (2025)

Figure 7: 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 completed; this probability peaks at completion, and then gradually decreases over time. These patterns are consistent with observed practices in the oil and gas industry, and validate the usage of satellite imaging datasets for flaring measurement.

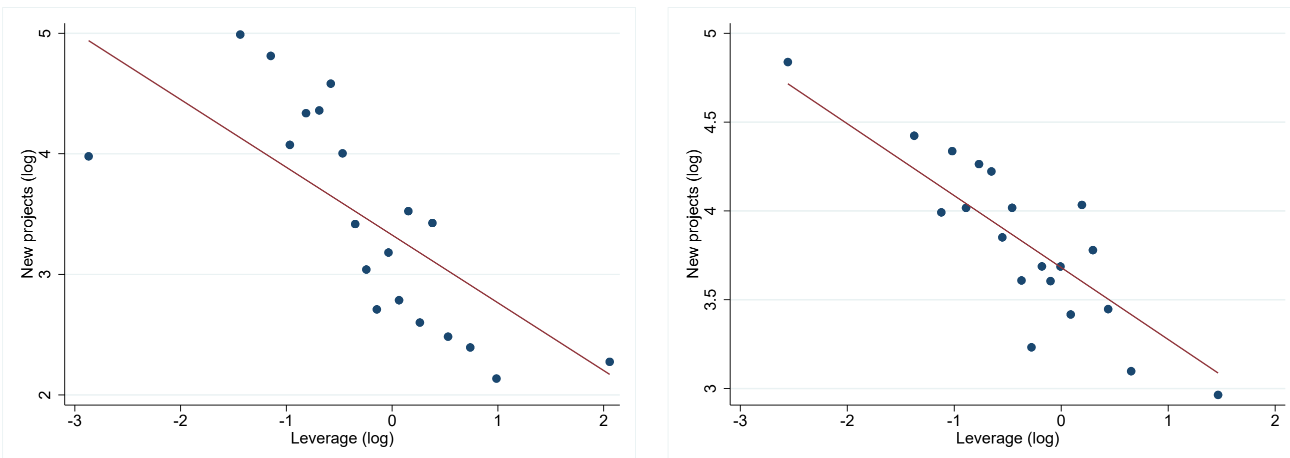
Figure 8: Relationship between New Projects and Financial Distress



These graphs plot the binscatter of the number of new projects, aggregated at the basin level, with the Altman's Z-score. Both graphs show a positive relationship between the number of new projects and the Z-score, consistent with the idea that firms that are more financially distressed are more likely to invest in fewer new projects. The graph on the left shows the relationship without any controls. The graph on the right shows 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.

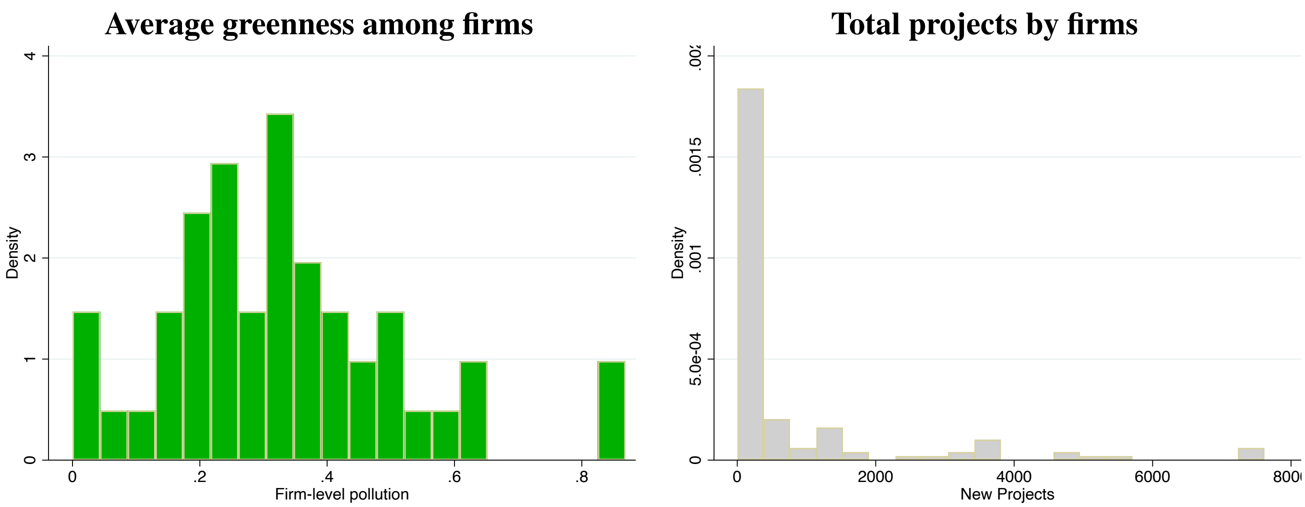
Figure 9: Relationship between New Projects and Leverage

Without controls With controls



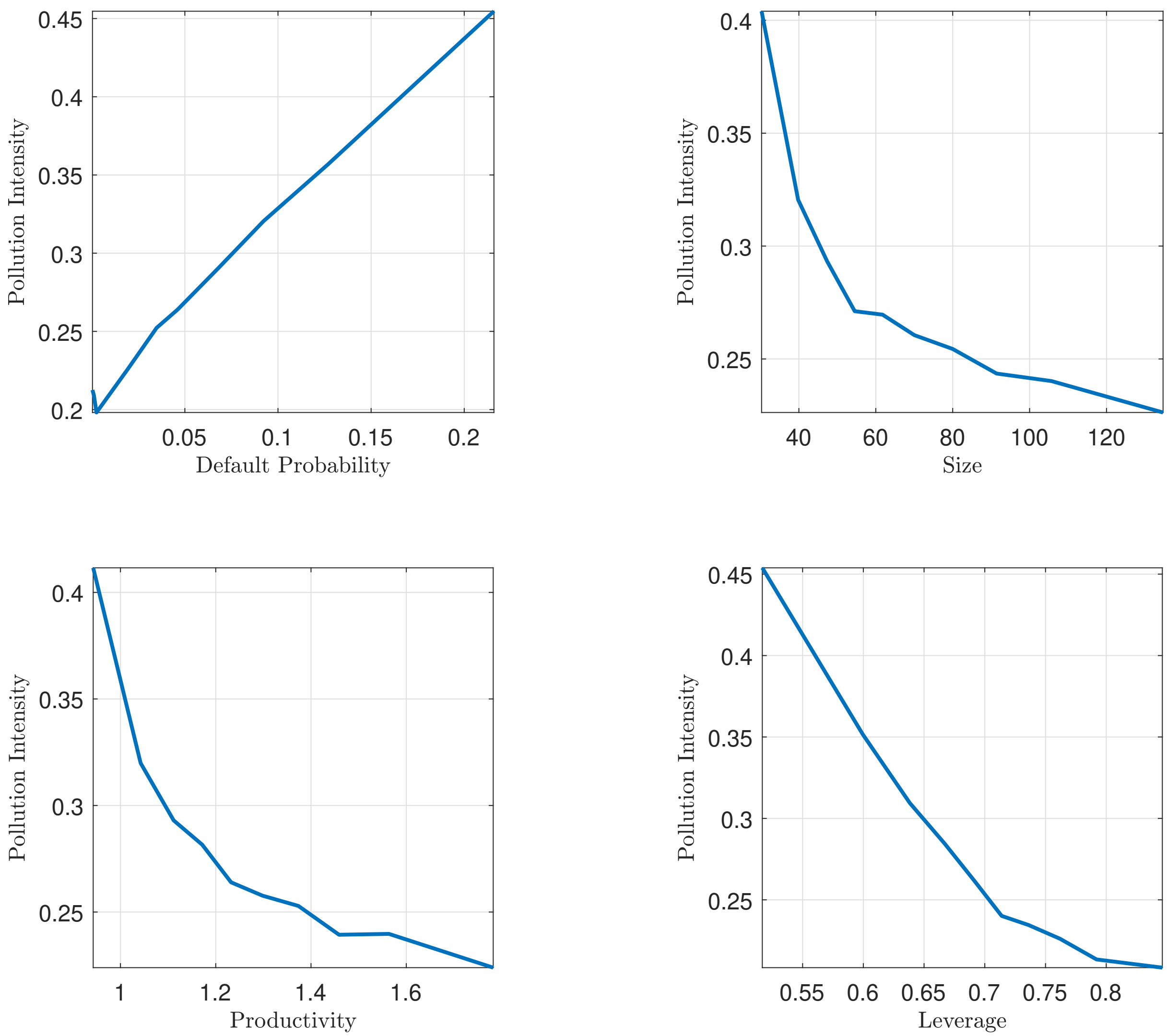
These graphs plot the binscatter of the number of new projects, aggregated at the basin level, with Altman's Z-score. Both graphs show a positive relationship between the number of new projects and the Z-score, consistent with the idea that firms that are more financially distressed are more likely to invest in fewer new projects. The graph on the left shows the relationship without any controls. The graph on the right shows 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 10: Distributions of Green Firms and Projects



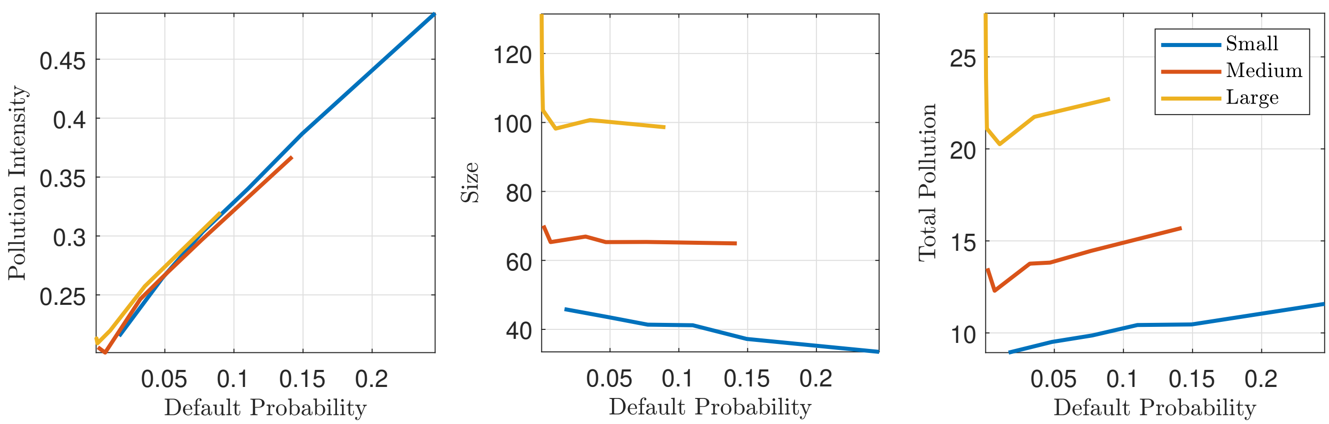
The graph on the left plots the average greenness among firms, which is the fraction of wells that were either using toxic chemicals or flaring between 2012 and 2022 in our sample. To limit the influence of outliers, we drop the firms that had fewer than 100 projects between 2012 and 2022. The graph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

Figure 11: Financial Distress and Pollution Intensity - Model



This figure shows the relationship between financial distress, as measured by 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. The parameter values are reported in Table 3. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Figure 12: 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 3. The results are obtained using a panel of 5,000 firms simulated over 30 years.

Table 7: Moment construction (1/3)

Variable	Value	Construction
Book leverage	.29	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then compute the ratio (Long-term debt (DLTT) + debt in current liabilities (DLC)) / total asset (AT). We winsorize the ratio at 5% and 95%. Finally, we take the average of this value.
Leverage	.759	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then compute the ratio (Long-term debt (DLTT) + debt in current liabilities (DLC)) / Stockholders Equity -Parent (SEQ). We winsorize the ratio at 5% and 95%. Finally, we take the average of this value.
Frequency of Equity Issuance	0.466	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We follow Huang and Ritter (2022) and construct a variable of Δ equity as follows: Sale of Common and Preferred Stock (sstk)- Purchase of Common and Preferred Stock (prstkc). We construct a variable of equity issuance that takes the value one if the variable Δ Equity is at least 5% of the book value of assets (at) and at least 3% of the market value of equity (csho $\times$ prcc_f) at the beginning of the year. Next, we take the rolling sum of the values for the last three years. Finally, we take the frequency when this rolling sum is above 0.
Ratio of Equity Issuance	.0806	This variable is calculated using the sample of Compustat for oil and gas extraction company (NAICS code 211) between 1990 and 2022. We follow Huang and Ritter (2022) and construct a variable of Δ equity as follows: Sale of Common and Preferred Stock (sstk)- Purchase of Common and Preferred Stock (prstkc). We divide this variable by total asset (at). We replace this variable by missing if the value is negative or above 1. We then replace this variable with 0 if the variable Equity issue is equal to 0 for that year.
Ratio of Debt issuance	.0906	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We follow Huang and Ritter (2022) and construct a variable of Δ debt as such: Long-Term Debt Issuance (dltis) - Long-term Debt- Reduction (dltr) - Current Debt - Changes (dlcch). We construct a variable of debt issuance that takes the value one if the variable Δ debt is at least 10% of the book value of assets (at) and at least 3% of the market value of equity (csho $\times$ prcc_f) at the beginning of the year. We replace Δ debt with 0 if the variable debt issuance is equal to 0. We replace the variable Δ debt as missing if the value is below 0 or above 1. We divide Δ debt by total asset (at) and take the average value over the whole sample.

Moment construction (2/3)

Variable	Value	Construction
Autocorrelation of sales ratio	.373	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then calculate the sale ratio as Revenue-Total (revt) / total assets (at). We winsorize the ratio at 5% and 95%. We drop the variables that are missing and the year 1991. Finally, if we have observations for less than 5 years, then we drop the company. We use this sample to calculate the mean and standard deviation. Then, we each firm, we calculate the autocorrelation of the sale ratio in year t with the sale ratio in year t-1. We take the average of all these autocorrelations to obtain the autocorrelation of sales ratio.
Mean of sale ratio	.343	See above
Sd of sale ratio	.21	See above
Average investment rate	0.172	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then calculate the following ratio: (Total asset in year t - Total asset in year t-1) / Total asset in year t. We winsorize the ratio at 5% and 95%, and take the average.
Size 1 Inv. Rate/ Avg. Inv. Rate	0.851	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then calculate the following ratio: (Total asset in year t - Total asset in year t-1) / Total asset in year t. We winsorize the ratio at 5% and 95%, which we call the investment rate. Next, for every year (except 1990), we sort the total assets into four quartiles. For every year (except 1990), we take the ratio of the average of the investment rate for the first quartile over the average of the investment rate for the fourth quartile.
Average pollution intensity (Firm-level)	.32	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We next match it to the sample of firms we can observe pollution practices. We then construct the variable pollution, which is a dummy variable equal to one if well is flared or uses toxic chemical, and zero otherwise. Finally, we take the sample average and the firm-level average of this variable.

Moment construction (3/3)

Variable	**Value**	**Construction**
Investment rate using project-level data	0.09	We use the sample of Compustat for oil and gas extraction companies (NAICS code 211) between 1990 and 2022. We then match it to the sample of firms for which we can observe their investment at the project level. Next, we take the average of the number of projects across firms and basins. Finally, we compute the average total number of projects at the firm level during the period. The investment rate is calculated using the following ratio: Average of yearly projects / Average of total project.

Table 8: 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 9: 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 one if the well is either flared or using toxic chemicals and zero, otherwise.