Shale Debt Structure and Pollution Control *

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Abstract

This paper analyzes how firms in the shale oil industry adjusted their production in response to green policy shocks, particularly after the Paris Agreement.We find that firms with high levels of short-term debt experienced significant refinancing challenges, reflected in reduced bond issuance, decreased bank new money injection, and higher cost of debt. By creating a novel index that measures toxic chemical usage at the well level and combining it with firm-level financial data, we use a difference-in-differences liked approach to demonstrate that high short-term debt ratio firms notably reduced their use of toxic chemicals following the policy change. Heterogeneity analyses reveal that financially healthier firms, firms with higher capital expenditure intensity, and those with more concentrated supplier bases exhibited greater pollution reductions. Changes in institutional ownership, particularly declines by banks and investment managers, further strengthened firms' environmental adjustments.

Keywords: Shale oil, Paris Agreement, Debt Financing, Financial Friction, Toxic Chemicals, Pollution Control.

JEL Classification: **G18, G32, D22, Q55, Q56**

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1 Introduction

The shale oil industry, which emerged in 2009, has rapidly become a dominant force in global oil production, now accounting for over half of the market. However, the hydraulic fracturing (fracking) methods used in shale oil extraction have been linked to environmental concerns, including the contamination of underground water with increased salt concentrations and non-biodegradable compounds, as well as the release of greenhouse gases. In light of rising environmental, social, and governance (ESG) concerns, along with heightened climate change awareness among policymakers and investors, there has been mounting pressure for industries—including shale oil—to adopt greener production practices. One such practice is the use of more environmentally friendly proppants in hydraulic fracturing processes. During periods of external green shocks or internal financial distress, firms may innovate in their exploitation methods or adopt alternative chemicals to mitigate their environmental impact. The increasing transparency provided by FracFocus, which discloses information about shale oil wells in 12 U.S. states, has enabled us to track the adoption of greener production practices by shale oil firms before and after the Paris Agreement.

This paper asks: Do firms that adopt greener production practices—measured by reduced toxic-chemical intensity—reap financial or operational benefits? Surprisingly, our results confirm that "greener" wells do not generate higher per-unit output: oil and gas production over both six- and twelve-month horizons is statistically indistinguishable across wells with high versus low toxic-chemical indices . If no production gains accrue, can environmental stewardship still pay off via improved access to credit or better financing terms?

To explore this, we examine two margins:

Syndicated-loan market reactions. We show that, despite heightened environmental scrutiny following the Paris Agreement, the average terms of new syndicated loans to shale oil firms—loan spreads, total commitment sizes, and overall credit availability—remained stable, with only modest shortening of maturities and no economically meaningful tightening of pricing .

Debt-dependence and pollution behavior. We construct a firm-level indicator of persistent short-term-debt reliance—capturing those firms with above-median ratios of short-term debt to assets across multiple pre-Paris years. Contrary to the notion that heavily indebted firms would "double down" on pollution when credit is tight, these firms in fact reduced their toxic-chemical usage more sharply than their less-levered peers post-Paris, cutting their chemical intensity by roughly 60. This suggests that financial constraints can spur, rather than deter, environmental improvements when future regulatory risks rise.

In further channel tests, we document that firms with greater capital-expenditure intensity or higher pre-Paris debt-service burdens show the largest post-Paris declines in chemical intensity; whereas firms with healthier balance sheets (higher Altman Z-scores or stronger interest coverage) and firms facing more concentrated supply chains also respond more vigorously to the same policy shock.

This paper contributes to the growing literature on how financial institutions and investors pursue non-financial objectives, with a particular focus on environmental goals. While this body of work spans various financial strategies aimed at achieving pro-social or political objectives, it also provides a critical lens through which to examine the role of financial markets in encouraging environmental responsibility.

A core area of this literature concerns capital allocation strategies employed by financial institutions to promote environmental sustainability. Several studies highlight the use of divestment and ESG investment strategies. For instance,(Green & Roth, 2025) discuss how capital allocation policies such as impact investing may support socially valuable firms. However, these approaches often face challenges in achieving meaningful impact, particularly if capital is easily substitutable. This is in line with (Broccardo, Hart, & Zingales, 2022), who argue that divestment strategies are often ineffective because capital flows can be easily diverted to other sources. Moreover, (Edmans, Levit, & Schneemeier, 2022) suggest that industry-specific tilting strategies could be more impactful than blanket divestment. Financial institutions also employ activist strategies to promote pro-environmental practices, including shareholder voting or policy interventions. However, such measures may only be effective when firms' activities are sensitive to changes in capital cost or availability. (Pastor, Stambaugh, & Taylor, 2023) explore the role of ESG strategies in shaping firms' decision-making, while (Hartzmark & Shue, 2023) contend that policies targeting capital supply are most effective when firms' operations are responsive to changes in funding costs. In this context, our study of the syndicated loan market and new corporate debt market after the Paris Agreement adds to the literature by highlighting the financing impact of green financial policies on shale oil firms.

This paper contributes to four strands of literature.

First, we extend the literature on the environmental impacts of hydraulic fracturing (HF) in shale oil production. Prior studies such as (Jackson et al., 2014), (Currie, Greenstone, & Meckel, 2017), and (Bonetti, Leuz, & Michelon, 2021) emphasize significant environmental risks associated with HF, particularly groundwater contamination due to non-biodegradable chemicals ((?, ?; Agarwal et al., 2020)). Additionally, (Christensen, Hail, & Leuz, 2021) document that disclosure mandates help mitigate pollution through increased public scrutiny. Our study complements this literature by developing a novel, granular toxic chemical usage index at the well-level using FracFocus data, enabling precise tracking and evaluation of environmental behavior in shale oil production.

Second, our paper contributes to research exploring the operational implications of adopting environmentally friendly production methods. Contrary to the prevailing assumption that greener practices naturally enhance operational performance, we find no significant production advantage for wells employing fewer toxic chemicals. This result challenges conventional wisdom by indicating that operational incentives alone may be insufficient to promote environmentally friendly practices.

Third, this study adds to the growing literature examining how external policy interventions influence firms' environmental decisions. Previous research highlights that mandatory ESG disclosures and climate regulations significantly shape corporate behavior ((Christensen et al., 2021; Kellogg, 2014)). We build on this evidence by analyzing how shale oil firms responded to the Paris Agreement, a major global climate policy. Specifically, we find that firms with high short-term debt reliance experienced greater refinancing difficulties after the policy shock, characterized by decreased bond issuance and reduced inflows of bank funding. Importantly, these financially constrained firms subsequently showed a pronounced reduction in toxic chemical usage, highlighting how external regulatory pressures can interact with internal financial frictions to produce meaningful environmental improvements.

Fourth, our analysis enriches the literature on the interplay between financial constraints and corporate environmental and social responsibility (CSR). Prior research provides mixed evidence regarding the relationship between financial constraints and CSR initiatives ((Cheng, Ioannou, & Serafeim, 2013; Attig, Cleary, El Ghoul, & Guedhami, 2013; Habib, Costa, Huang, Bhuiyan, & Sun, 2018; Chan, Chou, & Lo, 2017; Campbell, 2007)). We directly address this debate by showing that firms experiencing financial distress—especially those heavily dependent on short-term debt financing—respond more vigorously to environmental regulations by reducing pollution. Through detailed channel analyses, we further reveal that pollution reduction is more pronounced among financially healthier firms, those with higher capital expenditure burdens, those with concentrated supply chains, and firms experiencing ownership reductions by banks and investment managers. These findings underscore the importance of internal financial health, cost structure, supply-chain dynamics, and investor governance in shaping corporate responses to regulatory changes.

Collectively, by integrating detailed environmental data with firm-level financial and ownership characteristics, this study advances our understanding of the financial and institutional conditions under which external policies effectively incentivize corporate environmental responsibility.

The paper proceeds as follows. In Section 2, we provide background information for our study, including hydraulic fracturing and environment concerns. Section 3 describes the unique dataset. Section 4 we analysis of well level toxic properties. Section 5 introduce debt and loan market reaction on Paris Agreement. Section 6 explore potential channels. Section 7 offers Robustness test. Section 8 is the conclusion mark.

2 Background

In this section we will introduce the general research background regarding Hydraulic fracturing process and its environmental concerns.

Hydraulic fracturing and environmental concerns

The success of Shale Oil industry largely beneficial from technology advances, techniques like horizontal drilling, and hydraulic fracturing (HF). Operators adapts multiple chemicals for different purpose during fracturing. The fracturing process involves the injection of high-pressure ”fracking fluid”, normally consisting of water, sand and other proppants, into a well borehole in order to induce fractures in deep-rock formations. Consequently, this facilitates the more optimal movement of natural gas, petroleum, and brine. The fracturing process entails injecting high-pressure ”fracking fluid,” primarily composed of water and containing sand and other proppants, into a well hole to create cracks in deep-rock formations. This allows for the more efficient flow of natural gas, petroleum, and brine. Upon removal of hydraulic pressure, small grains of hydraulic fracturing proppants, such as sand or aluminum, maintain the fractures' openness (Von Estorff & Gandossi, 2015). Further more, chemical usage in HF works have effects on productivity of well, making the designing of fracturing fluid for optimal performance based on the shale layer properties of vital importance.

While hydraulic fracturing offers economic benefits through increased hydrocarbon accessibility, opponents argue that it poses environmental risks, including water contamination, noise and air pollution, and potential seismic activity, along with public health concerns. Typically concerns include the chemicals present in HF fluids and the substantial volumes of wastewater generated by the process (Currie et al., 2017).

The potential HF fluid hazardous on health and environment has prompted regulatory measures. From government disclosure, in the United Kingdom, environmental regulators permit only nonhazardous chemicals to be used, prioritizing the protection of underground water sources. Similar introduction of disclosure standards for HF wells and fracturing fluids also appears in several U.S. states. Since 2010, various state-level legislation requirements have been introduced, mandating HF operators to disclose the chemical composition of their fluids. Disclosure mandates lead to reduced pollution per unit of production, decreased use of toxic chemicals, and fewer spills and leaks of HF fluids and wastewater. (Christensen et al., 2021)

3 Data and Variables

This section contains comprehensive information on each data source. The comprehensive well-level data on production chemical usage and job starting date enable us to evaluate toxic chemical usage. By analyzing granular data on well-level productivity, location, and land use properties integrating chemical toxicity data, we can determine the harmful properties of production fluids at the drilling level. In addition, we collect and analyze data on the hazardous properties of operators. By matching project-level data with firm measurements, we are able to establish a connection between the financial performance of enterprises and their production decisions.

3.1 Well-level data.

FracFocus, founded in 2011, has been dedicated to documenting the chemicals used in hydraulic fracturing activities around the country. More than 1,600 companies have reported chemicals used in more than 189,000 hydraulic fracturing operations. The detailed reporting regarding, initiated hydraulic fracturing date, well vertical distance, latitude and longitude geolocation, operators, federal land use, chemical purpose, chemical usage percentage in fracturing volumes, etc. We keep the sample period afterwards. We drop the disclosure which is (i) with no meaningful completion date (starting date is later than the ending date), (ii) error chemical usage information (e.g. with negative or 0 chemicals usage information, or the sum of the chemicals proportion usage is larger than 110 or lesser than 80). (iii) For each year, we keep states with new exploitation wells larger than 5 for the estimation robustness. (iv) For the consistency in production characteristics, We focus on oil wells with production type labeled with 'OIL' and 'OIL & GAS'. From the general exploitation properties side, both private firm and public firm, voluntary disclosure and local legal forced disclosure are taken into consideration; 61,259 disclosures are defined.

3.2 Chemicals data.

To evaluate the toxic information of the chemicals used during hydraulic fracturing. We first listed all the unique chemicals identified with the Chemical Abstract Service identification number (CAS number) disclosed by FracFocus. CAS number, proposed by CAS registry, has identifies to each substance that appears in the literature. The purpose is to avoid the hassle of having multiple names for a chemical and to make it easier to search the chemical information. A CAS number can be divided into three parts, with the first part up to seven digits and second part two digits, third part a single digit as a check digit, each part is connected by hyphens (format like: xxxxxxx-xx-x). We firstly drop Fracfocus disclosed CAS number do not matched the format, and then check whether the formed CAS number exists or validates, 1191 chemicals are defined authentic.

In spite of new chemicals, business secrete products, or no mandatory disclosure requirement by the local governments, using CAS numbers we can find chemicals' Materials Safety Data Sheet (MSDS) which is a comprehensive document that offers specific information on workplace safety and health related to the use of various chemicals and chemical products.. We use the MSDS information disclosure by ChemicalBook website.

The Globally Harmonised System of Classification and Labelling of Chemicals (GHS) show in the MSDS is a globally acknowledged benchmark overseen by the United Nations. Its purpose was to consolidate and substitute the several hazardous substance categorisation and labelling methods hitherto employed globally. The standardised labels including:

(i) Symbols or GHS hazard pictograms, including information of environment concerns and human health hazard information which assigned to multiple GHS hazard codes. The detailed 9 categories are shown in Table 3 B.

(ii) Two signal words (”Danger” and ”Warning”) are defined to highlight danger and hazard levels. Out of the 1191 chemicals we have chosen, 528 are classified as dangerous, 458 are labeled as warnings, and 205 do not have any signal words.

(iii) Other key information like Hazard statement(s), Precautionary statement(s) are hard to determine which are not taken into consideration.

The GHS hazard pictograms allow us to explore toxic fluids chemical properties from each sub-categories, expressively from health and environmental hazardous perspectives. The signal words provides the hazardous degree of each chemicals. Based on these information, we are able to calculate fluid toxic index for each disclosure.

3.3 Firm-level data.

To address firm level financial performance's impact on production decision, we download core financial characteristics of the public traded oil and gas firms in Compustat. As Fracfocus received information from both public traded firms and private firms, Firstly we use fuzzy matching to match the Fracfocus 'OperatorName' with Compustat 'conm', we then manually find out the determined public traded firm lists. Secondly, we set Global industry classification standard 'ggroup' as 1010.0 for the selection of the energy industry. Thirdly, we keep public firms which have continue exploitation activity between the time period of 2012 to 2019. [1] We find 46 matched energy firms.Then we calculate the financial indicators used for determinate financial constraints and for further corporate level controls.

Firm level financial performance may related to market leverage, Tobin's Q, others observable dimensions like profitability, dividends, cash flow (in millions), sales growth etc. We use these information to capturing financial constraining firms.

3.4 Loan and debt data

We use Dealscan database to evaluate the overall loan market behaviors. We focous loans starting date within 2012-2019 and the data cleaning process we follow (Green & Vallee, 2024), we assign shares equally accross banks for those syndicating loans without detailed transaction amount information. We only focus on debt for general purpose usage rather than specifically aims. [2] We also use Refinitiv SDC new debt issue database to evaluate firm level debt issuance situation.

4 Toxic Chemicals

Fracturing fluids are injected into the well to generate conductive fractures and circumvent damage close to the wellbore in zones containing hydrocarbons. This procedure greatly enhances the productive surface area of the reservoir compared to its condition before fracking. A variety of chemical additives are used to ensure the fluid has specific characteristics such as viscosity, friction reduction, compatibility with the formation, and control over fluid loss.

[1]The fracfocus established in 2011, but the state level of disclosure start from 2012, to make the time series estimation more robust, we drop the first disclosure year.

[2]Debt with specific purpose are like Merge, Acquisition, Leverage buyout, Exit financing, Trade financing, IPO related financing, Dividend or Distribution to Shareholders

4.1 Purpose with toxic and chemical usage

The process of hydraulic fracturing utilises two primary types of substances: fracturing fluids and proppants. The fluids traditionally employed in shale well fracturing treatments consist of either water-based solutions or mixed slickwater fluids. The latter refers to water-based fluids that are blended with friction-reducing additives such as potassium chloride. Determining the appropriate fracturing fluids, additives, and proppants is a subjective procedure that takes into account elements such as formation assessment, laboratory test findings, and project expertise. The most fundamental and widely used technique for stimulating wells in unconventional gas extraction is slickwater fracturing. Chemical additives used in hydraulic fracturing have several purposes and are categorised into subgroups including fluid-loss additives, clay stabilisers, gel breakers, bactericides or biocides, and pH control agents. The objective of acidisation is to augment the productivity or injectablity of a well.

Proppants, usually consisting of sand or synthetic sand-like minerals like silica sand, resin-coated silica sand or artificial ceramics, are employed to maintain the openness of fractures, therefore facilitating the movement and subsequent extraction of crude oil and natural gas. The efficacy of a proppant is assessed based on its capacity to preserve fracture conductivity, and the successful choice of a proppant is established by attaining substantial fracture continuity. In terms of production time, the rate of production decreases more quickly with higher proppant sizes, since it is alone determined by the permeability of the formation matrix. In addition to fracture conductivity, additional important considerations for choosing proppants in multistage fracturing are flow convergence in transverse fractures, proppants transport in low-viscosity fluids, and proppants compression usually at low concentrations.

To categorize and determine the specific uses of toxic chemicals during the fracturing process, we consulted the chapters in the Handbook of Hydraulic Fracturing. (Speight, 2016) Initially, we cataloged the types of chemicals used and their intended purposes as outlined in the handbook, followed by employing fuzzy matching with the disclosed purposes from the frac-focus dataset. We retained the results of this type matching for further analysis. The keywords used for matching are listed in the appendix. Our goal is to identify which purposes involve the use of toxic chemicals more frequently and which purposes have been reducing their use of toxic chemicals over the past decade.

Figure 4 provides a detailed visualization of the application of toxic chemicals, identified by the hazard designation 'Danger', across diverse fracturing operations from the year 2011 onwards. Each cell within the heatmap is color-coded to reflect the count of distinct toxic chemicals employed, with the color gradient transitioning from blue, denoting a lower count, to red, indicating a higher count. The analysis of the heat map yields several pertinent observations: (i) There was a notable peak in the employment of unique toxic chemicals during the period 2013 to 2015. (ii) The subsequent reduction in the diversity of toxic chemicals used is likely attributable to the implementation of stricter regulatory frameworks and enhanced transparency in chemical disclosure. (iii) The data exhibit considerable variability in chemical utilization across different operational purposes; functions such as Acid Treatment, Bactericides/Biocides, Corrosion Inhibitors, General Additives, Surfactants, and Scale Inhibitors consistently demonstrate higher chemical diversity. (iv) A significant reduction in the utilization of toxic chemicals within each categories suggests an ongoing industry shift towards reducing the use of hazardous substances in these specific applications.

4.2 Toxic Index

To address the toxic chemicals usage for each well, we proposed toxic index for each well i.

$$Toxic\_Index_{i,t} = \sum_{i} \left(PercentHFJob_{i,j,t} \times 1_{\{j \in \text{toxic}\}} \right) \tag{1}$$

Where, $PercentHFJob_{i,j,t}$ represents the proportion of ingredient j in the total hydraulic fracturing volume, expressed as a percentage by mass. The term $1_{\{j \in \text{toxic}\}}$ denotes the indicator function, which is assigned a value of 1 if chemical j is labeled with the 'Danger' signal word, and 0 otherwise. For those chemicals defined dangerous but not environmental hazardous such as Crystanile silica/SIO2 are not taken into calculation. [3]

[3]For those chemicals with signal word 'Danger' we deep down to search their GHS classifications. Mainly found Sillicons related chemicals are less harmful to both environments and human beings. While other chemicals such as CA2O3, NIOx, some are water solvable or can be searched with impacts such as fishes.

To address the right skewness of the chemical index, we follow the approach outlined by (Fetter, 2022). Firstly, we apply a logarithmic transformation to the index, adding 0.01 to avoid taking the log of zero. Subsequently, we winsorize the data at the upper 1% level to mitigate the impact of outliers.

Figure 5 shows the yearly distribution of well level toxic index. We find that in general decreasing trend in well level toxic chemical use. The lower percentile decreases after 2015, while the upper percentile decreases in the year 2015 to 2018 but reverts to the previous period after.

4.3 Toxic Chemical Properties

Hydraulic Fracturing process causes environmental and health concerns over toxic usage which leads to state governments either force the HF operators to disclose their exploitation to FracFocus and local state agency or just banned the HF outright. so will being green bring oil productive surplus or will federal land usge will lead more constraints to the toxic chemical usage.

Property 1: Federal lands do not significantly reduce pollution levels despite having strict regulations and monitoring systems in place.

Federal lands, owned and administered by the U.S. federal government, are essential for the country's management of natural resources. Oil companies are required to secure leasing rights from the federal government to conduct exploration and extraction activities on these lands. These leases are allocated through competitive auctions and are governed by contracts that impose rigorous environmental and safety standards. As a result, oil extraction activities on federal lands are subject to an array of federal environmental regulations [4]. These regulatory frameworks are designed to safeguard environmental quality and public health, which can lead to restrictions or delays in the approval and execution of oil extraction projects. Furthermore, federal agencies such as the Bureau of Land Management (BLM) and the U.S. Forest Service (USFS) are tasked with overseeing the development of these resources. Policy shifts, including limitations on drilling and hydraulic fracturing

[4] Typically regulations including the Clean Air Act and the Clean Water Act, as well as environmental impact assessments mandated by the National Environmental Policy Act (NEPA)

which have a significant impact on the pace and scale of oil production. In addition, the federal government levies rents, royalties, and production sharing fees on oil companies, which not only constitute a substantial portion of the operational costs but also provide significant revenue streams for the federal treasury. We explore the relation between federal land and well chemical usage using following empirical model:

$$Toxic\_Index_{i,j,s,t} = \alpha + \beta_1 \times Federal_i + \gamma_t + \theta_j + \delta_s + \epsilon_{i,j,s,t} \quad (2)$$

where $Toxic\_index_{i,j,t}$ is well i's toxic chemical usage percnetage owned by firm j in geoloation s at time t,$Federal_i$ is an indicator of whether well i exploited in federal land,γ_t is year fixed effect, θ_j is the firm fixed effect, δ_s is the geo-location grid fixed effect, the geo-location is the grid by 1×1 degree latitude and longitude changes.

[Insert Table 5 here]

Table 5 shows that there is no relation between federal land and well chemical use, local federal governments do not promote well's green behavior possibly due to stronger censor restrictions and regulatory requirements.

Property 2: A green well brings no production surplus.

Operators engage in resource exploitation to maximize economic benefits. To examine whether adopting greener practices leads to production advantages over medium- and long-term horizons, we estimate the following regression model:

$$Production_{i,j,s,t} = \alpha + \beta_1 \times Toxic\_Index_{i,j,s,t} + \gamma_t + \theta_j + \delta_s + \epsilon_{i,j,s,t} \quad (3)$$

where $Production_{i,t}$ is the logarithm of the gross gas (oil) production within t period average standardized by perforated foot, $t \in \{6 \text{ month}, 12 \text{ months}\}$, $Toxic\_index_{i,j,t}$ is well i's toxic chemical usage percnetage owned by firm j in geoloation s at time t,γ_t is year fixed effect, θ_j is the firm fixed effect, δ_s is the geo-location grid fixed effect, the geo-location is the grid by 1×1 degree latitude and longitude changes.

Regression results presented in Table 5, columns (2) and (3), indicate that wells utilizing fewer toxic chemicals—i.e., "greener" wells—do not exhibit higher production levels in either the short or long term. This suggests that reducing toxic chemical usage does not provide a production surplus.

5 Debt Market and Firm reaction to Paris Agreement

Following the 2015 Paris Agreement, oil and energy companies have faced intensified regulatory and financial constraints aimed at reducing carbon emissions. Governments, institutional investors, and financial intermediaries have increasingly incorporated environmental considerations into lending and investment decisions, exerting mounting pressure on fossil fuel-dependent industries.

In particular, the loan and debt markets provide a direct lens into these emerging financial frictions. Loan agreements and debt issuance activities are critical financing channels for energy firms, and shifts in credit terms—such as pricing, availability, maturity structures, and covenants—reflect lenders' reassessment of long-term risks associated with carbon-intensive industries.

In this section, we explore how the Paris Agreement has reshaped the loan and debt financing environment for energy companies. We examine changes in syndicating loan and corporate debt market to assess the extent to which financing conditions have tightened relative to firm with high short-term debt ratios for their intensive financing needs. Our analysis provides early evidence of how climate-related regulatory commitments affecting firms' access to capital and potentially altering the production strategies.

5.1 The Corporate Debt Market

Firms heavily dependent on short-term debt are more likely to be affected by financing pressures in the aftermath of the Paris Agreement due to their frequent need to roll over debt. To identify firms that rely more heavily on short-term debt prior to the Paris Agreement, we construct a time-invariant firm-level indicator, $1\{\text{ST\_Debt}_j\}$, based on firms' historical shortterm debt usage patterns. Specifically, for each fiscal year up to 2015 includes, we classify firms whose ratio of short-term debt to total assets exceeds the cross-sectional median as being "above median" for that year. We then count, for each firm, the number of years in which it was classified as above median. Firms in the top 50% based on this count are assigned a value of one for $1\{\text{ST\_Debt}_j\}$, indicating persistent high reliance on short-term debt; all others are assigned a value of zero. This indicator remains fixed across all years in our analysis, ensuring that it reflects pre-Paris Agreement financing structures rather than post-event adjustments. We use the following regression to test Paris Agreement's impact on high short-term debt ratio firms' new debt issuance.

$$NewDebtProperty_{i,j,t} = \alpha + \beta_1 \times Pairs \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{i,j,t} \tag{4}$$

where $NewDebtProperty_{i,j,t}$ is firm j's new debt i's properties at time t including Logarithm of Debt Amount, Debt spread, $Paris$ is an indicator of years after paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, $\delta_{j,t}$ is the firm controls, γ_j is firm fixed effect, θ_t is the time fixed effect.

Regression result are shown in Table 6. A negative coefficient on $Paris \times ST\_Debt$ in $Column(1)$, indicates that firms with higher short-term debt reliance experienced a larger reduction in debt issuance volume after the Paris Agreement. In contrast, a positive coefficient in $Column(2)$, suggests that these firms faced higher borrowing costs in the post-Paris period. These results provide evidence that firms with frequent refinancing needs became more financially constrained following the Paris Agreement.

[Insert Table 6 here]

5.2 The Syndicated Loans Market

After the paris agreement, (Green & Vallee, 2024) find that banks are divesting money from coal industries. Many NGOs have listed list of bank who are willing to exit the fossil fuel market by the year of 2030. Also from share holders view, stocks holding by more green investors force the fossil fuel firms taking green trasitions. In this sector, we discuss what is the real loan market for the shale oil industry after the Paris Agreement.

$$LoanProperty_{i,j,l,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \lambda_{j,l} + \phi_t + \epsilon_{i,j,l,t} \tag{5}$$

where $LoanProperty_{i,j,l,t}$ is debt i's properties including Debt Term, Logarithm of Loan

Amount, Debt spread borrowed by oil firm j with lender l at time t. $Paris$ is an indicator of whether the debt is issued after paris agreement,$1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, $\lambda_{j,l}$ is the borrower lender fixed effect, ϕ_t is the year fixed effect.

Result in Table 7 shows that, relative to other firms, high short-term debt firms significantly extended the maturity of their loans after the Paris Agreement (Column 1), likely in response to increased refinancing risks. However, the total new loan amount did not change materially (Column 2), while the amount of new money raised from bank declined sharply (Column 3), suggesting that these firms faced tightened credit constraints. The loan spread did not exhibit significant differences (Column 4), implying that the tightening was primarily on bank's new money injection rather than the price of credit.

[Insert Table 7 here]

5.3 Firm level Cost of Debt

We calculate firm level's pre tax cost of debt by interest and related expense divided by total debt. We find that after 2015, ST_Debt firms facing a sever debt financing friction.

Figure 1 plots the average cost of debt for high- and low-DLC firms over 2012–2020. Before 2015, cost trajectories were relatively stable and parallel across both groups. However, following 2015, high-DLC firms experienced a significant rise in debt costs, surpassing low-DLC firms by 2016. This divergence suggests that short-term debt-dependent firms were more exposed to financing frictions or shifts in credit conditions. Interestingly, the gap temporarily narrowed around 2018–2019.

To further validate this, we run the following subgroup regression.

$$CostofDebt_{-j,t} = \alpha + \beta_1 \times Prais + \delta_j + \epsilon_{j,t} \tag{6}$$

where $CostofDebt_{-j,t}$ is the cost of debt of operator j in year t. $Paris$ is paris agreement dummy, δ_j is firm level fixed effect.

Table 9 reports the heterogeneity analysis of firm-level cost of debt in response to the Paris Agreement. Column (1) includes all firms, the coefficient on the Paris dummy is positive and statistically significant at the 5% level (0.0092), suggesting that, on average, firms experienced an increase in their cost of debt following the Agreement.

In Columns (2) and (3), we split the sample based on firms short term debt leverage. The effect is concentrated in ST-Debt firms (Column 2), where the coefficient increases to 0.0118 and remains significant at the 10% level, while the effect becomes statistically insignificant and economically smaller in the case of non-short-term debt firms (Column 3). This pattern indicates that firms more reliant on short-term debt faced greater financing frictions following the Paris Agreement.

[Insert Table 8 here]

5.4 Short-term Debt Firm Pollution Control

We now explore the pollution heterogeneity for the short-term debt firms and other firms by the following equations

$$Toxic\_Index_{i,j,s,g,t} = \alpha + \sum_{k=2012}^{2019} \beta_k \times 1\{\text{ST\_Debt}_j\} \times Year_k + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t} \quad (7)$$

$$Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t} \quad (8)$$

where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are more short term debt financers $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect.

Regression result are shown in 8, We find that prior to the Paris Agreement, there was no systematic difference in toxic chemical usage between firms with high and low short-term debt ratios. Following the Agreement, high-ST debt firms significantly reduced their toxic chemical usage, with the effect strengthening over time. This suggests that financially constrained firms were more responsive to the regulatory shift induced by the Paris Agreement, adjusting their pollution behaviors to mitigate financing risks. The estimated coefficient on the interaction term suggests an economically significant reduction of approximately 0.931 less logarithmic percentage chemical usage (approximately 60% less).

[Insert Table 9 here]

6 Channel Test

6.1 Financial Cost

Firms that face higher internal financial costs may have stronger incentives to adjust operations, including environmental practices, to optimize resource allocation and minimize costs, particularly after external regulatory shocks such as the Paris Agreement.

High short-term debt (ST) firms, due to their heightened sensitivity to financing conditions, may respond to environmental regulation not merely through liquidity management but also by adjusting costly operational aspects such as pollution control measures.

Measures of Financial Costs

- **Capital Expenditure Intensity (Capex/Assets)**: We measure a firm's investment intensity by the ratio of capital expenditures (Capex) to total assets (AT). Higher Capex/AT indicates greater capital intensity, suggesting larger fixed obligations and potentially higher financial rigidity.
- **Administrative Expense Burden (Log(SGA/Sale))**: We measure administrative cost exposure by the logarithm of selling, general, and administrative expenses (SGA) over sales. A higher value reflects heavier overhead cost structures, which may pressure firms to manage other operating costs, including environmental liabilities.

Results and Interpretation

The regression results presented in Table 10 show differentiated responses across these financial cost measures.

In Column (1), ST firms with greater capital expenditure intensity (Capex/AT) exhibit a significant and economically large reduction in toxic chemical usage following the Paris Agreement. This suggests that capital-intensive ST firms are more aggressive in adjusting pollution practices.

In contrast, Column (2) shows that ST firms with higher administrative cost burdens (Log(SGA/Sale)) slightly increase their pollution intensity after the Paris Agreement. One possible explanation is that firms already burdened with high fixed administrative costs may have limited flexibility to further invest in pollution reduction technologies, leading to worsened environmental outcomes under financial pressure. Overall, the results highlighting an important channel through which internal financial frictions shape corporate environmental behavior.

[Insert Table 10 here]

6.2 Financial Health

To further explore the relationship between financial performance and environmental outcomes, we examine firm-level financial ratios using three distinct measures: the Altman Z-score, the Interest Coverage Ratio, and the Loughran McDonald Constraints Ratio (LM ratio). These metrics capture different aspects of a firm's financial health, allowing us to disentangle the effects of balance sheet strength, debt servicing ability, and textual indicators of financial constraints on pollution behavior.

By incorporating these financial indicators, we aim to investigate whether firms with stronger financial positions behave differently from financially constrained firms in response to the Paris Agreement. Specifically, we assess whether firms with greater financial flexibility—either through lower bankruptcy risk, stronger debt repayment capacity, or fewer textual constraints—exhibit distinct environmental behaviors compared to their more constrained counterparts.

Altman Z-score

Altman Z-score is a financial metric used to assess a firm's likelihood of bankruptcy. It is calculated as a weighted sum of several financial ratios and is particularly useful for evaluating manufacturing firms. The higher the Z score, the lower risk of bankruptcy. The formula is given in appendix.

Interest Coverage Ratio

Another related financial metric is the Interest Coverage Ratio, which measures a company's ability to meet its interest obligations with definition of EBIT divided by Interest Expense. A higher interest coverage ratio indicates a stronger ability to service debt, reducing financial distress risk.

Loughran McDonald Constraints Ratio

The Loughran McDonald Constraints Ratio (LM ratio) is proposed by (Bodnaruk, Loughran, & McDonald, 2015), which using the constraining word frequency in 10-K file to measuring firm level financial constraints through a textual view. Firstly, we obtained public firms' 10-K file from SEC-EDGAR. We then use NLTK python package to sparse the 10-k, pre-processing including dropping punctuation, non english words and stop words. After the pre-processing process, we use regular expression operations to find the constraining words proposed by LM [5]. The LM ratio is defined as the words frequency of constraining words divided by total words counts. The higher the LM ratio, the higher the firm constraints.

We re-estimate the regression from Section 5 within different financial characteristic groups. The results, presented in Table 11, reveal several key findings.

First, regarding the Altman Z-score classification, we find that ST firms with a higher Altman Z-score (Column 1), which indicates stronger balance sheets and lower bankruptcy risk, experience a statistically significant decrease in toxic chemical usage following the Paris Agreement (coefficient = -0.66651, significant at the 10% level). In contrast, ST firms with a lower Altman Z-score (Column 2) do not exhibit significant changes in pollution behavior. This suggests that financially healthier firms are more responsive to environmental policy changes.

Second, when splitting by the Interest Coverage (IC) ratio, a similar pattern emerges. ST Firms with higher IC ratios (Column 5), indicative of stronger debt-servicing capacity, significantly reduce their toxic chemical usage after the Paris Agreement (coefficient = -0.85080, significant at the 10% level). Conversely, ST firms with lower IC ratios (Column 6) show no statistically significant response. This again underscores that financially flexible firms are more proactive in adjusting their environmental behavior in response to regulatory pressure.

Taken together, these results imply that financial health plays a critical role in shaping ST firms' environmental responses. ST Firms with stronger financial positions, characterized by lower bankruptcy risk, stronger debt service capacity, and fewer textual financial

[5] The LM constraining words are available from University of Notre Dame

constraints, are more capable of and more likely to reduce environmental externalities when facing global regulatory shifts such as the Paris Agreement. Financial flexibility appears to facilitate investments in cleaner technologies or operational adjustments needed to comply with environmental expectations.

[Insert Table 11 here]

6.3 Reputation Risk

In the context of our study, high short-term debt (ST) firms may adjust their pollution behaviors not solely due to direct compliance costs but also to mitigate potential reputational losses following the Paris Agreement. Firms with higher exposure to reputational risks could have stronger incentives to proactively reduce pollution to preserve their public image and sustain investor confidence.

Measures of Reputation Risk

To capture different dimensions of reputation risk, we employ three complementary firm-level metrics:

- **Reputation Risk Index (RRI)**: We use the Reputation Risk Index (RRI) obtained from the WRDS database. This index aggregates firm-level exposure to reputational concerns across various dimensions, including environmental incidents, governance controversies, and public perception. A higher RRI indicates greater reputational risk.

- **ESG Score**: As a broader measure of firm sustainability practices, we use the Refinitiv Industry-Adjusted ESG Score. This score evaluates a firm's overall performance across environmental, social, and governance factors, adjusting for industry-specific characteristics. Higher scores reflect better ESG practices and, presumably, lower exposure to reputation-based penalties.

- **Environmental Pillar Score (E Pillar)**: To isolate the environmental dimension, we include the Environmental Pillar Score from Refinitiv. Higher scores denote stronger environmental performance.

We re-estimate the baseline regression by intersection reputation terms and the regression results are presented in Table 12. Column (1) shows that among high-ST firms, those with higher RRI experience a statistically significant reduction in toxic chemical usage after the Paris Agreement. This finding suggests that firms more exposed to reputational risks are more responsive to environmental regulation by reducing pollution intensity, consistent with reputation preservation motives. Yet, Columns (2) and (3) focus on ESG and Environmental Pillar scores, we don't find similar result.

Overall, the evidence indicates that reputational concerns indeed play a role in moderating firms' environmental responses. However, the effect appears more pronounced when directly using incident-based reputation metrics (RRI) than broader ESG scores.

[Insert Table 12 here]

6.4 Supply Chain Risk

Environmental risk management is not solely an internal operational matter but also increasingly intertwined with firms' supply chain structures. A firm's ability to control environmental outcomes can be affected by the concentration and diversity of its supplier base. In the context of high short-term debt (ST) firms, tighter or riskier supply chains may constrain the flexibility needed to implement pollution control measures following regulatory shocks like the Paris Agreement.

Firms facing greater supply chain risks may either preemptively adjust pollution behaviors to ensure operational continuity, or, conversely, find themselves unable to respond effectively due to supply bottlenecks.

Measures of Supply Chain Risk

We construct two complementary measures to capture the nature of firms' supply chain exposure:

- **Supplier HHI (Herfindahl-Hirschman Index)**: The Supplier HHI is calculated annually for each operator (firm) by aggregating the squared market shares of each supplier, where market share is defined as the proportion of wells serviced by a particular supplier within the operator's total wells in year t.

$$HHI_{j,t} = \sum_{s=1}^{S_{j,t}} \left(\frac{N_{s,j,t}}{N_{j,t}} \right)^2 \tag{9}$$

where:

- $S_{j,t}$ is the number of unique suppliers associated with operator j in year t,
- $N_{s,j,t}$ is the number of wells serviced by supplier s for operator j in year t,
- $N_{j,t} = \sum_{s=1}^{S_{j,t}} N_{s,j,t}$ is the total number of wells operated by j in year t.

The term $\frac{N_{s,j,t}}{N_{j,t}}$ represents the market share of supplier s within operator j's total well operations in year t. A higher value of $HHI_{j,t}$ indicates greater supplier concentration (i.e., reliance on fewer suppliers), while a lower value indicates a more diversified supplier base.

- **Supplier Count (Supcount)**: Supplier Count measures the number of unique suppliers each operator engages with in a given year. A higher supplier count reflects greater supplier diversity and lower exposure to supply disruptions, providing firms with greater operational flexibility.

Results and Interpretation

The regression results presented in Table 13 illustrate the differential responses of ST firms based on their supply chain characteristics. Column (1) shows that ST firms with higher Supplier HHI—meaning more concentrated supply chains—experience a significantly larger reduction in toxic chemical usage after the Paris Agreement (coefficient = -1.27903, significant at the 1% level). This finding suggests that firms relying heavily on a few key suppliers may proactively reduce pollution risks to avoid disruptions and preserve critical supply relationships under increasing environmental scrutiny. In Column (2), Supcount term is positive and significant. This implies that firms with more diversified supplier bases are less responsive in reducing pollution.

[Insert Table 13 here]

6.5 Ownership Risk

Beyond internal financial health and supply chain characteristics, changes in the ownership structure of firms can also influence corporate environmental behavior. Ownership dynamics, particularly among institutional investors, may alter firms' incentives and capacity to respond to regulatory shocks such as the Paris Agreement.

In this section, we investigate how changes in ownership shares by different types of institutional investors affect pollution outcomes among high short-term debt (ST) firms.

Data and Definition of Ownership Change Variables

We obtain institutional ownership data from the WRDS 13F Holdings database, which records quarterly equity holdings of large institutional investors. Following standard practice, we aggregate quarterly data to the annual level and compute annual ownership percentage changes for each firm-year observation.

We further classify institutional investors into five types based on the TYPECODE variable:

- **Type 1: Bank** — commercial and investment banks
- **Type 2: Insurance Company** — life and property insurance firms
- **Type 3: Investment Companies and Their Managers** — mutual funds and fund management companies
- **Type 4: Investment Advisors** — independent advisory firms managing assets on behalf of clients
- **Type 5: Others** — pension funds, university endowments, foundations, and other institutional investors

For each type, we define two main variables:

- *change.typek*: the annual change in ownership percentage by investor type k.
- *paris.debt.cownk*: an interaction term capturing the joint effect of the Paris Agreement, high ST debt exposure, and the change in ownership by type k.

Results and Interpretation

The estimation results are presented in Table 14.

In the post-Paris Agreement period, for firms with high short-term debt exposure, a reduction in ownership by bank investors (Type 1) is associated with a significant decline in toxic chemical usage. Similarly, a decrease in ownership by investment companies and their managers (Type 3) also leads to a substantial reduction in pollution. In contrast, changes in ownership by other types of institutional investors (Types 2, 4, and 5) have weaker or statistically insignificant effects on environmental outcomes. These findings suggest that the withdrawal of key institutional investors, particularly banks and investment companies, may have heightened firms' incentives to reduce pollution, possibly due to increased financing constraints or reputational pressures. By comparison, ownership changes among other types of investors appear to exert more limited governance effects.

[Insert Table 14 here]

7 Robustness Test

7.1 Placebo Test with a Random Shock

To further validate the identification strategy and rule out potential pre-existing trends or spurious correlations, we conduct a series of placebo tests. For each placebo year from 2012 to 2019, we create a pseudo-treatment variable that equals one for firms classified as having a high short-term debt ratio (ST_Debt) starting from that year, and zero otherwise. We then estimate the same baseline specification:

$$Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Shock + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t} \quad (10)$$

where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are more short term debt financers, Shock is a dummy variable mean a random shock year before or after the paris agreement, $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect.

The logic is straightforward: if our baseline results are driven by a genuine exogenous shock from the Paris Agreement, placebo policy shocks assigned to other years should not yield significant treatment effects.

Figure 3 plots the estimated placebo treatment effects with their 95% confidence intervals across years. The figure shows that the estimated placebo effects fluctuate randomly around zero before 2015, without strong systematic pre-trend. After 2015, the coefficients shift downward consistently, indicating a genuine policy impact beginning with the Paris Agreement. The visual evidence supports the parallel trends assumption and reinforces the credibility of our difference-in-differences estimation. Overall, the placebo tests provide robust support for our identification strategy.

The absence of systematic pre-trends and the sharp negative shift after 2015 both confirm that the Paris Agreement serves as an exogenous shock to firms' pollution behaviors, particularly for those with higher short-term debt exposure.

8 Conclusion marks

This paper investigates how shale oil firms, particularly those with high short-term debt reliance, adjusted their pollution behaviors following the Paris Agreement. Using detailed well-level toxic chemical usage data and firm-level financial information, we assess the environmental and financial responses to this major global climate policy.

Our findings reveal several important insights. First, reducing toxic chemical usage does not yield production advantages for shale oil firms, suggesting that greener production practices are not incentivized through operational gains. Second, financial flexibility plays a critical role in shaping environmental outcomes: highly indebted firms, especially those facing greater refinancing pressures, exhibit more significant reductions in pollution intensity after the Paris Agreement, consistent with the notion that financial constraints amplify environmental responsiveness. Third, through channel analyses, we show that firms with higher internal financial costs (such as capital intensity) or stronger financial health (measured by Altman Z-score and interest coverage) are more responsive to environmental regulations. Moreover, reputation risk exposure, particularly measured by the Reputation Risk Index (RRI), strengthens firms' incentives to engage in greener production, while broader ESG scores are less predictive. Finally, supply chain concentration (higher supplier HHI) also motivates firms to reduce pollution under regulatory pressure, while changes in institutional ownership, particularly declines by banks and investment managers, further encourage pollution reduction.

Overall, our study highlights the interplay between financial structures and environmental behaviors in response to global climate agreements. The results imply that financial constraints, reputational considerations, and supply chain structures critically shape corporate environmental strategies, offering valuable implications for policy makers aiming to align financial incentives with environmental goals.

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JobSYear StateName	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	sum
Alabama	0	0	5	17	0	0	0	0	0	0	0	0	0	0	170
California	0	0	0	25	73	41	0	0	0	0	0	0	0	0	150
Colorado	0	72	732	1226	1023	494	462	601	341	0	0	0	0	0	393
Kansas	0	0	31	138	43	0	0	13	22	7	0	9	0	0	418
Louisiana	0	0	0	6	0	0	0	0	0	0	0	0	0	0	52
Montana	0	0	53	68	15	0	0	0	0	0	0	8	0	0	243
New Mexico	0	12	252	265	186	102	61	92	160	100	438	726	432	74	582
North Dakota	16	54	1035	1829	1212	453	442	464	444	242	287	320	489	35	643
Ohio	0	0	225	374	344	141	205	116	149	149	132	113	81	8	676
Oklahoma	0	19	974	1574	730	397	348	328	204	90	177	251	276	19	638
Pennsylvania	0	0	0	0	12	0	0	0	0	0	0	0	0	0	38
Texas	16	251	5630	7344	3582	1674	2007	2395	2917	1519	2401	2941	2884	531	672
Utah	0	0	329	549	94	27	77	70	54	27	0	37	51	14	751
West Virginia	0	0	0	0	0	0	0	0	0	5	37	22	30	0	136
Wyoming	0	18	102	135	99	17	18	16	68	16	23	0	23	26	550
sum	97	349	738	783	601	474	468	536	482	413	290	369	288	224	6112

Table 1: Disclosure Count by State and Year

JobSYear StateName	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024
Alabama	0	0	41	44	0	0	0	0	0	0	0	0	0	0
California	0	0	0	27	24	24	0	0	0	0	0	0	0	0
Colorado	0	32	33	28	22	20	18	20	23	0	0	0	0	0
Kansas	0	0	29	24	6	0	0	36	38	38	0	38	0	0
Louisiana	0	0	0	26	0	0	0	0	0	0	0	0	0	0
Montana	0	0	44	32	36	0	0	0	0	0	0	10	0	0
New Mexico	0	31	33	39	34	30	26	23	15	9	14	15	13	9
North Dakota	30	30	33	30	32	31	27	20	19	15	15	12	13	16
Ohio	0	0	30	25	21	24	32	36	33	28	15	25	34	35
Oklahoma	0	25	27	24	24	23	36	41	30	24	19	16	19	11
Pennsylvania	0	0	0	0	19	0	0	0	0	0	0	0	0	0
Texas	19	30	32	28	24	22	24	23	22	28	29	21	19	15
Utah	0	0	41	41	38	53	52	45	33	29	0	30	4	9
West Virginia	0	0	0	0	0	0	0	0	0	12	18	18	20	0
Wyoming	0	26	26	24	20	10	19	24	28	24	35	0	22	17

Table 2: Medium Chemical Number Count by State and Year

Table 3 A: Chemicals Signal Word Statistics

Table 3 panel A reports the summary statistics of well-level information based on production type clustered in state level. Table 2 panel B reports the summary statistics of median unique chemicals usage for each production type clustered in state level since 2010.

Variables	OBS	Danger	Warning	No Description
Signal Words	1191	528	458	205

Table 3 B: Hazard Class Pictograms

Table 3 panel B reports the meaning of GHS code. For each chemical with unique CAS Number, the MSDS reports its GHS information, which provide not only dangerous level but also hazardous classification.

GHS Code	**Meanings**
GHS01	Explosives
GHS02	Flammables
GHS03	Oxidizers
GHS04	Compressed Gasesl
GHS05	Corrosives
GHS06	Acute Toxicity
GHS07	Irritant
GHS08	Health Hazard
GHS09	Environment

Table 4: Financial Indicators and Calculation Methods

Table 4 listed the financial indicators we use to capturing firm level financial distress and their detailed calculation methodoloy.

Financial indicators	**Calculation methods**
K	PP&E - Total Net
CashFlow (in Millions)	Income Before Extraordinary Items (Cash Flow) + Depreciation and Amortization
Cash	Cash + Marketable Securities Adjustment
Dividened	Dividends - total
Tobin's Q	market value of equity plus debt divided by book assets.
Debt	Long-Term Debt – Total + Debt in Current Liabilities
Total capital	Debt plus total stockholders' equity

Table 5: Toxic Properties

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,t} = \alpha + \beta_1 \times Federal_i + \gamma_t + \theta_j + \delta_s + \epsilon_{i,t}$ where $Toxic\_index_{i,j,t}$ is well i's toxic chemical usage percnetage owned by firm j in geoloation s at time t,$Federal_i$ is an indicator of whether well i exploited in federal land,γ_t is year fixed effect, θ_j is the firm fixed effect, δ_s is the geo-location grid fixed effect, the geo-location is the grid by 1×1 degree latitude and longitude changes. For columns (2) and (3) was estimated by $Production_{i,j,s,t} = \alpha + \beta_1 \times Toxic\_Index_{i,j,s,t} + \gamma_t + \theta_j + \delta_s + \epsilon_{i,j,s,t}$ where $Production_{i,t}$ is the gross gas (oil) production within t period average standardized by perforated foot, $t \in \{6\text{ month}, 12\text{ months}\}$, Standard errors are clustered at operator level and given in parentheses.

	(1)	(2)	(3)
	Toxic Index, 1	Log prod_6	log prod_12
Federal Well	0.09540		
	(0.12170)		
Toxic Index, 1		-0.00054	0.00380
		(0.01158)	(0.01178)
Log True Vertical Depth	-0.01482	0.15417***	0.14237***
	(0.03678)	(0.04843)	(0.04380)
Log Horizontal Length	0.08952**	-0.36636***	-0.31549***
	(0.04200)	(0.04713)	(0.04796)
Log Water Volume	-0.24489***	0.12571***	0.12233***
	(0.04525)	(0.02585)	(0.02574)
Obs.	63761	61115	61123
R^2	0.474	0.425	0.462
Year FE	Y	Y	Y
Geo FE	Y	Y	Y
Firm FE	Y	Y	Y

Table 6: New Debt Issue Property

The table shows the the estimation of the following panel fixed effect regression: $NewDebtProperty_{i,j,t} = \alpha + \beta_1 \times Pairs \times 1\{\text{ST\_Debt}_j\} + \delta_{j,t} + \gamma_j + \theta_t + \epsilon_{i,j,t}$ where $NewDebtProperty_{i,j,t}$ is firm j's new debt i's properties at time t including Logarithm of Debt Amount, Debt spread, $Paris$ is an indicator of years after paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, $\delta_{j,t}$ is the firm controls, γ_j is firm fixed effect, θ_t is the time fixed effect. Standard errors are clustered at year_month level and are given in parentheses.

	(1)	(2)
	lg_debt_amount	spread
Paris×ST_Debt	-0.33998**	0.81524**
	(0.14784)	(0.36972)
Log(at)	-0.00001**	-0.00002**
	(0.00000)	(0.00001)
Profit	-0.97753**	-0.20579
	(0.45993)	(1.97353)
Debt	-0.00000	0.00001
	(0.00001)	(0.00002)
Market_Leverage	0.69383	1.55442
	(0.42107)	(1.55179)
Q	-0.13382	0.60708
	(0.17976)	(0.43890)
Z	0.05424	-0.26070
	(0.08769)	(0.21647)
Sale/at	0.08302	-1.34858***
	(0.14742)	(0.48051)
Interest_expense	-0.00034	0.24852
	(0.00236)	(0.29925)
Mean Dep.Var.	6.291	2.243
Obs.	360	213
R^2	0.768	0.830
Firm FE	Y	Y
Year FE	Y	Y

Table 7: Syndicated Loan Market Property

The table shows the the estimation of the following panel fixed effect regression: $LoanProperty_{i,j,l,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \lambda_{j,l} + \phi_t + \delta_p + \epsilon_{i,j,l,t}$ where $LoanProperty_{i,j,l,t}$ is debt i's properties including Debt Term, Logarithm of Loan Amount, Debt spread borrowed by oil firm j with lender l at time t. $Paris$ is an indicator of whether the debt is issued after paris agreement,$1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, $\lambda_{j,l}$ is the borrower lender fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at borrower-lender level and given in parentheses.

	(1) debt_term	(2) lg_debt_amount	(3) lg_new_money	(4) spread
Paris$\times$$ST_Debt$	0.49833**	0.01524	-1.34878***	-0.17264
	(0.24070)	(0.03025)	(0.29262)	(0.12766)
Mean Dep.Var.	3.973	3.430	5.705	1.895
Obs.	2426	2426	355	2100
R^2	0.545	0.960	0.813	0.650
Borrower-Lender FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Figure 1: Average Cost of Debt

Table 8: Firm Pollution Heterogeneity

We use the following empirical model to explore firm pollution heterogeneity. $Toxic\_Index_{i,j,s,g,t} = \alpha + \sum_{k=2012}^{2019} \beta_k \times 1\{\text{ST\_Debt}_j\} \times Year_k + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ and $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1)	(2)
	Toxic Index, 1	Toxic Index, 1
2012×*ST_Debt*	-0.03083	
	(0.77074)	
2013×*ST_Debt*	0.06607	
	(0.17513)	
2015×*ST_Debt*	-0.59840*	
	(0.35009)	
2016×*ST_Debt*	-1.12673***	
	(0.39762)	
2017×*ST_Debt*	-1.23909***	
	(0.45519)	
2018×*ST_Debt*	-1.47415***	
	(0.49670)	
2019×*ST_Debt*	-1.98622**	
	(0.82742)	
Paris×*ST_Debt*		-0.93108***
		(0.25000)
Log True Vertical Depth	0.06923	0.05780
	(0.06510)	(0.06329)
Log Horizontal Length	0.17487**	0.17439**
	(0.06558)	(0.06589)
Log Water Volume	-0.21541***	-0.21697***
	(0.05030)	(0.05060)
Log(Total Asset)	-0.39190	-0.37408
	(0.29420)	(0.30979)
Q	-0.82353***	-0.89646***
	(0.28567)	(0.30766)
Capex/Total Asset	2.14273*	1.89804
	(1.13542)	(1.20775)
Profit	1.09497*	0.80358
	(0.59001)	(0.57461)
Dividend/Total Asset	-15.50089	-24.98672
	(13.43388)	(16.06096)
Tangibility	-1.06886	-1.22267
	(1.53719)	(1.74916)
Log(SGA/Sale)	0.29675**	0.18140
	(0.13644)	(0.13032)
Delta_Sale	0.25266	0.19923
	(0.21931)	(0.22745)
Mean Dep.Var.	-1.630	-1.630
Obs.	24474	24474
R^2	0.551	0.545
Year FE	Y	Y
Operator-supplier FE	Y	Y
Geo FE	Y	Y

Table 9: Firm cost of debt Heterogeneity

We use the following empirical model to explore firm cost of debt heterogeneity. $CostofDebt_{-j,t} = \alpha + \beta_1 \times Prais + \delta_j + \epsilon_{j,t}$, where $CostofDebt_{-j,t}$ is the cost of debt of operator j in year t. $Paris$ is paris agreement dummy, δ_j is firm level fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1) CostofDebt All	(2) CostofDebt ST_Debt	(3) CostofDebt nonST_Debt
paris	0.00923**	0.01183*	0.00479
	(0.00439)	(0.00585)	(0.00528)
lgat	-0.00000	-0.00000	-0.00000
	(0.00000)	(0.00000)	(0.00000)
profit	-0.01319	-0.02391	-0.00273
	(0.01509)	(0.02683)	(0.01160)
Market_Leverage	-0.00788	-0.01339	0.00119
	(0.01466)	(0.02360)	(0.01742)
Constant	0.05858***	0.05568***	0.06394***
	(0.00685)	(0.01057)	(0.00430)
Mean Dep.Var.	0.056	0.052	0.062
Obs.	332	212	120
R$\hat{2}$	0.461	0.443	0.500
Firm FE	Y	Y	Y

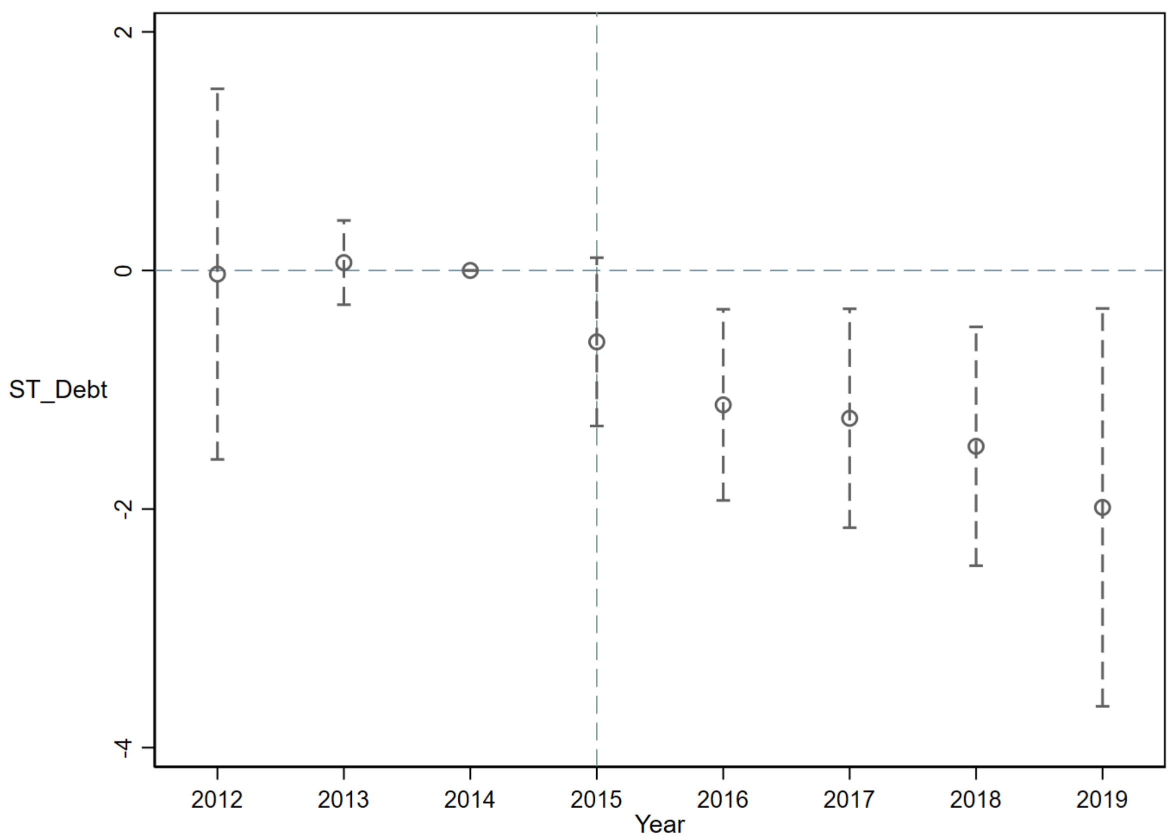

Figure 2: Parallel Trend for Policy Shock

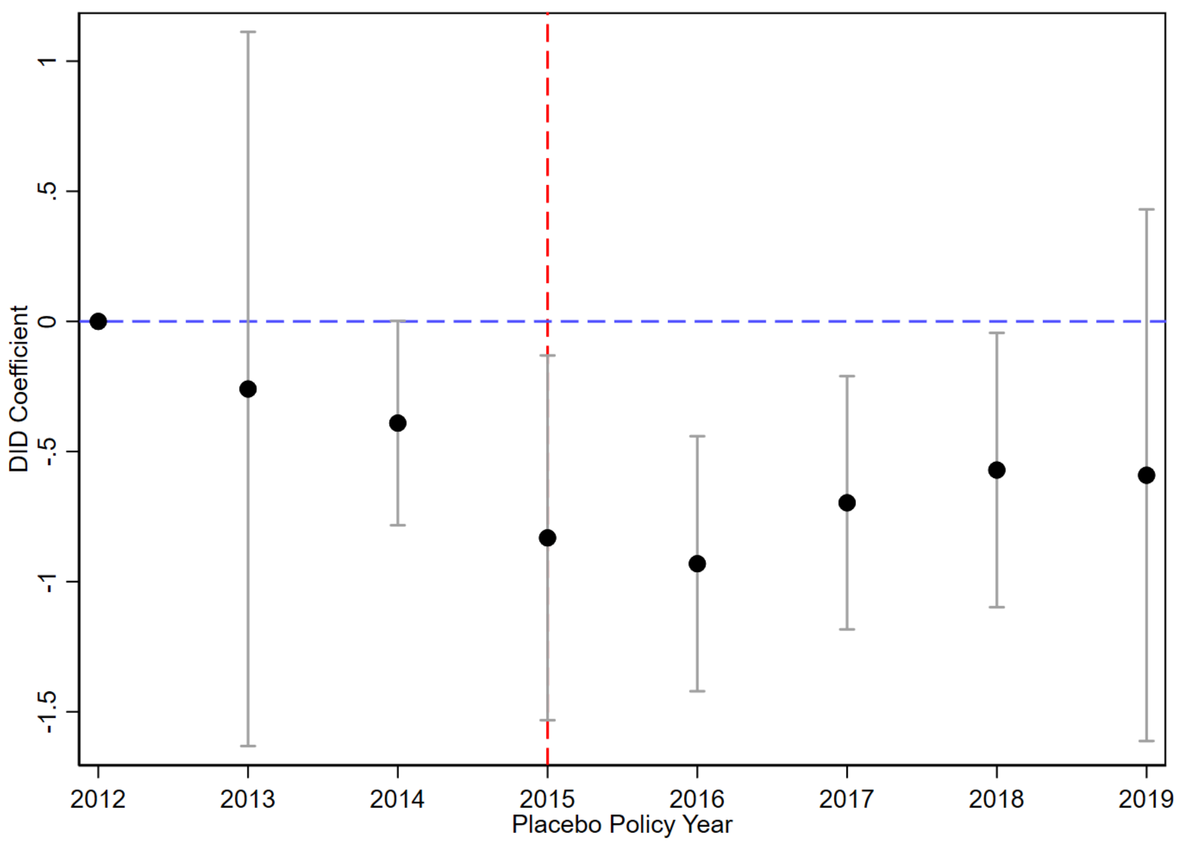

Figure 3: Placebo test for Policy Shock

Table 10: Financial Risks

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times Financial_{j,t} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers, $Financial_{j,t}$ is firm year level Financial indicator, $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1) Toxic Index, 1 b/se	(2) Toxic Index, 1 b/se
Paris_STDebt_Capex/at	-5.53611***	
	(1.82240)	
Paris_STDebt_Log(SGA/Sale)		0.07092***
		(0.02177)
Log True Vertical Depth	0.06163	0.05199
	(0.06125)	(0.06278)
Log Horizontal Length	0.16416**	0.17780**
	(0.06572)	(0.06697)
Log Water Volume	-0.21737***	-0.21526***
	(0.04967)	(0.05009)
Log(Total Asset)	-0.24741	-0.27253
	(0.33196)	(0.29820)
Q	-0.82776**	-0.89684***
	(0.32338)	(0.32613)
Capex/Total Asset	2.77836*	2.29772*
	(1.45061)	(1.32300)
Profit	1.07042*	0.75489
	(0.59415)	(0.55339)
Dividend/Total Asset	-21.78384	-24.75136
	(17.07256)	(16.19483)
Tangibility	-1.37387	-1.35604
	(1.78117)	(1.78274)
Log(SGA/Sale)	0.16846	0.19397
	(0.12776)	(0.13247)
Delta_Sale	0.20773	0.19495
	(0.21885)	(0.22357)
Mean Dep.Var.	-1.630	-1.630
Obs.	24474	24474
R$\hat{2}$	0.543	0.544
Year FE	Y	Y
Operator-supplier FE	Y	Y
Geo FE	Y	Y

Table 11: Financial Performance and Financial Constraints

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1) Toxic Index, 1 High Altman Z	(2) Toxic Index, 1 Low Altman Z	(3) Toxic Index, 1 High LM ratio	(4) Toxic Index, 1 Low LM ratio	(5) Toxic Index, 1 High IC ratio	(6) Toxic Index, 1 Low IC ratio
Paris×*ST_Debt*	-0.66561**	-0.13899	-0.53271***	-0.44164**	-0.28632	-0.85008***
	(0.29071)	(0.32294)	(0.17216)	(0.20172)	(0.20043)	(0.29181)
Log True Vertical Depth	0.06335	0.16241***	0.16804**	0.05954	0.05881	0.19484**
	(0.09314)	(0.04712)	(0.07885)	(0.06900)	(0.08001)	(0.09202)
Log Horizontal Length	0.17327*	0.06423*	0.16705***	0.08832**	0.16341*	0.10063*
	(0.08590)	(0.03733)	(0.05812)	(0.04030)	(0.09033)	(0.05456)
Log Water Volume	-0.19010**	-0.21563***	-0.19496**	-0.17413***	-0.18386**	-0.21142***
	(0.06864)	(0.03824)	(0.07092)	(0.03553)	(0.07499)	(0.04086)
Log(Total Asset)	-0.21805	0.02761	0.55003	-0.39328	0.15412	-0.03264
	(0.68820)	(0.19044)	(0.69676)	(0.23986)	(0.26847)	(0.22245)
Q	-0.79166*	-0.74154***	0.03956	-0.72058***	-0.21513	-0.84209***
	(0.39920)	(0.21243)	(0.15157)	(0.24131)	(0.42872)	(0.23737)
Capex/Total Asset	3.97131	-0.22568	0.34062	0.38287	1.69411	0.52434
	(3.02960)	(0.60610)	(1.08825)	(0.86335)	(1.57205)	(0.62984)
Profit	2.49020***	-0.81858*	-1.75008***	0.43522	0.36251	-0.08637
	(0.87669)	(0.41399)	(0.52922)	(0.49324)	(1.35338)	(0.50977)
Dividend/Total Asset	-11.08183	8.28682	-20.91443	2.80470	-13.63518	22.90786
	(14.29413)	(16.48904)	(20.16430)	(9.82799)	(14.10636)	(15.26541)
Tangibility	-1.74766	1.37876	-1.62319	0.77507	0.63862	1.39143*
	(1.84712)	(1.05871)	(1.89262)	(0.79203)	(2.30585)	(0.74744)
Log(SGA/Sale)	0.30128**	-0.15976	0.05848	-0.08470	0.04564	0.02651
	(0.13505)	(0.11165)	(0.20093)	(0.08620)	(0.12279)	(0.10015)
Delta_Sale	0.76264*	-0.17402	-0.54073***	-0.05491	0.26940	-0.15875
	(0.41905)	(0.10347)	(0.13473)	(0.18864)	(0.31432)	(0.17107)
Mean Dep.Var.	-1.650	-1.586	-1.519	-1.678	-1.501	-1.807
Obs.	16774	7695	7409	17061	14140	10325
R^2	0.535	0.683	0.398	0.641	0.501	0.691
Year FE	Y	Y	Y	Y	Y	Y
Operator-supplier FE	Y	Y	Y	Y	Y	Y
Geo FE	Y	Y	Y	Y	Y	Y

Table 12: Reputation Risks

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times Rep_{j,t} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers, $Rep_{j,t}$ is firm year level reputation risk, $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1) Toxic Index, 1	(2) Toxic Index, 1	(3) Toxic Index, 1
Paris_STDebt_RRI	-0.01745*		
	(0.00957)		
RRI	-0.00438		
	(0.00894)		
Paris_STDebt_ESG		-0.06701	
		(0.06594)	
ESG Score		0.10023	
		(0.09012)	
Paris_STDebt_E			-0.12251
			(0.09762)
E Score			0.07939
			(0.10243)
Log True Vertical Depth	0.05436	0.05368	0.04884
	(0.06390)	(0.06194)	(0.05947)
Log Horizontal Length	0.18900**	0.16121**	0.16408**
	(0.07604)	(0.07345)	(0.07438)
Log Water Volume	-0.22457***	-0.22223***	-0.22152***
	(0.05698)	(0.05599)	(0.05575)
Log(Total Asset)	-0.18645	0.23371	0.16382
	(0.34221)	(0.37627)	(0.37472)
Q	-0.83126**	-0.56744	-0.65001*
	(0.39162)	(0.34625)	(0.37097)
Capex/Total Asset	3.02309**	3.18586*	3.38977*
	(1.43655)	(1.63289)	(1.73132)
Profit	1.10990*	1.25146	1.29919
	(0.61051)	(0.77388)	(0.77329)
Dividend/Total Asset	-25.17786	-21.64952	-18.73476
	(15.25199)	(15.38392)	(14.18243)
Tangibility	-1.77348	-1.41174	-1.42883
	(1.86492)	(1.90918)	(1.93785)
Log(SGA/Sale)	0.19724	0.28329***	0.30854***
	(0.13029)	(0.09522)	(0.09239)
Delta_Sale	0.11755	0.32544	0.36805
	(0.23433)	(0.27477)	(0.24869)
Mean Dep.Var.	-1.661	-1.655	-1.655
Obs.	22384	20852	20852
R2̂	0.549	0.514	0.514
Year FE	Y	Y	Y
Operator-supplier FE	Y	Y	Y
Geo FE	Y	Y	Y

Table 13: Supply Chain Risks

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times supplyChain_{j,t} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers, $supplyChain_{j,t}$ is firm year level reputation risk, $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1)	(2)
	Toxic Index, 1	Toxic Index, 1
Paris_STDebt_HHI	-1.27903***	
	(0.13714)	
HHI	-0.03824	
	(0.32460)	
Paris_STDebt_Supcount		-0.01281
		(0.01640)
Supcount		0.05642**
		(0.02224)
Log True Vertical Depth	0.07847	0.04555
	(0.06704)	(0.05876)
Log Horizontal Length	0.15652**	0.16471**
	(0.06271)	(0.06585)
Log Water Volume	-0.21602***	-0.21744***
	(0.05243)	(0.04925)
Log(Total Asset)	-0.20818	-0.06909
	(0.28637)	(0.30803)
Q	-0.59150**	-0.76736**
	(0.22432)	(0.33917)
Capex/Total Asset	1.44920	2.52643
	(1.00409)	(1.53507)
Profit	0.92915	0.81930
	(0.58897)	(0.54637)
Dividend/Total Asset	-27.06045**	-27.02501
	(13.19541)	(19.32902)
Tangibility	-0.89880	-1.25215
	(1.59082)	(1.78600)
Log(SGA/Sale)	0.14510	0.14035
	(0.12519)	(0.12071)
Delta_Sale	0.13228	0.06335
	(0.22857)	(0.21448)
Mean Dep.Var.	-1.630	-1.630
Obs.	24474	24474
R^2	0.550	0.539
Year FE	Y	Y
Operator-supplier FE	Y	Y
Geo FE	Y	Y

Table 14: Ownership Change

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times \Delta ownership_{j,o,t,t-1} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i with operator j at state s exploited in year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable meaning for whether firms are mojre long term debt financers, $\Delta ownership_{j,o,t,t-1}$ is firm year level ownership percentage change based on type o, $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect λ_g is state level fixed effect, ϕ_t is the year fixed effect. Standard errors are clustered at operator level and are given in parentheses.

	(1)	(2)	(3)	(4)	(5)
	Toxic Index, 1	Toxic Index, 1	Toxic Index, 1	Toxic Index, 1	Toxic Index, 1
paris_debt_cown1	-27.69002***				
	(10.10514)				
change_type1	9.73835**				
	(4.41970)				
paris_debt_cown2		-16.14981			
		(26.61532)			
change_type2		-3.45049			
		(8.91893)			
paris_debt_cown3			-79.42280**		
			(34.82777)		
change_type3			11.09880		
			(11.41962)		
paris_debt_cown4				0.97010	
				(3.78155)	
change_type4				3.75470**	
				(1.50393)	
paris_debt_cown5					4.12939*
					(2.17880)
change_type5					0.43566
					(0.76799)
Mean Dep.Var.	-1.661	-1.661	-1.661	-1.661	-1.661
Obs.	20938	20938	20938	20938	20938
R^2	0.523	0.515	0.519	0.520	0.516
Well Control	Y	Y	Y	Y	Y
Operator Financial Control	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Operator-supplier FE	Y	Y	Y	Y	Y
Geo FE	Y	Y	Y	Y	Y

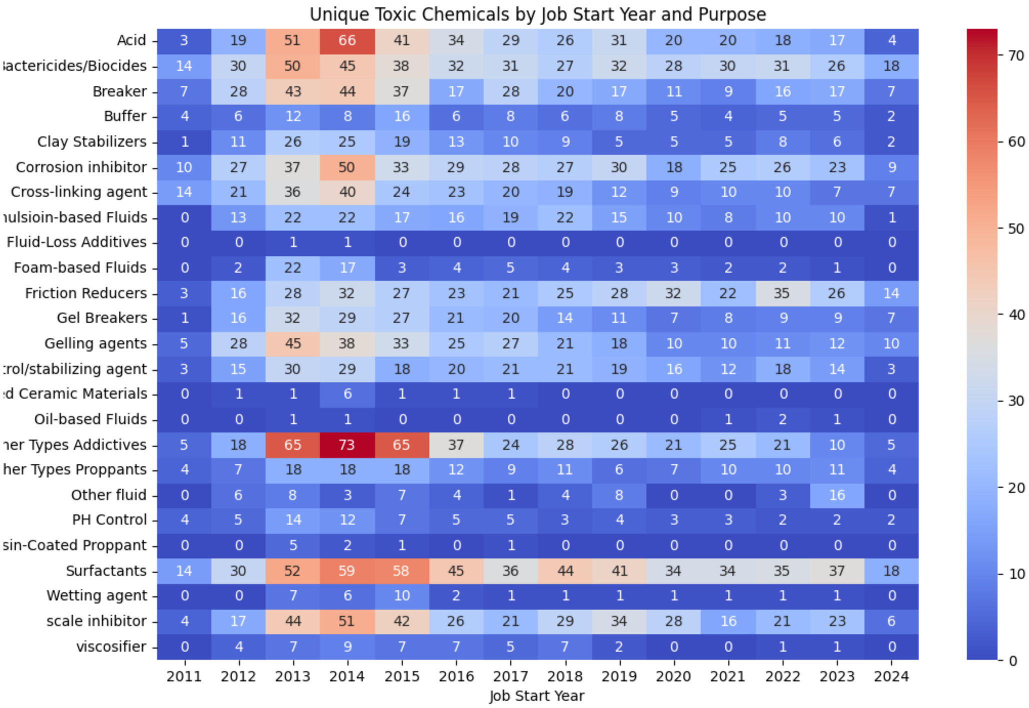

Figure 4: Toxic chemicals usage type per year classified by purpose

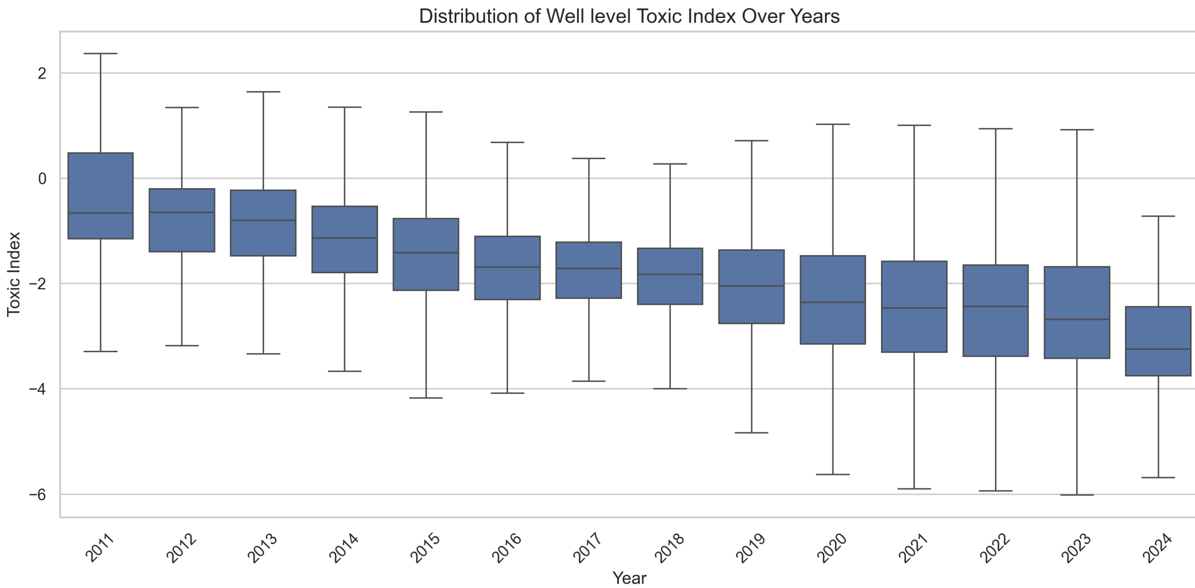

Figure 5: Toxic Index Distribution

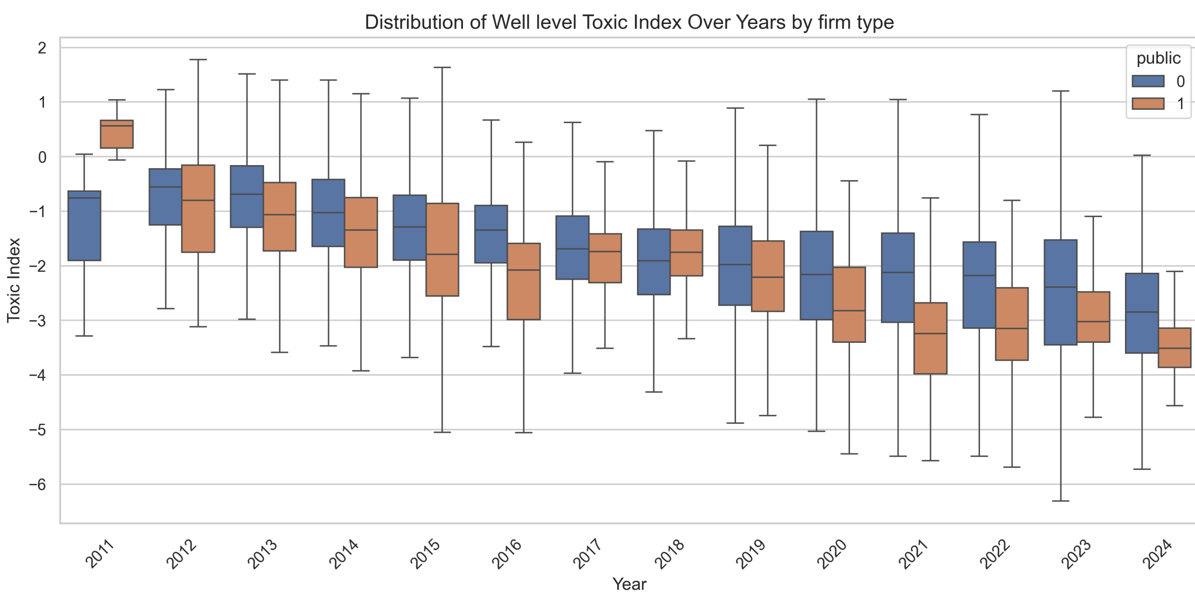

Figure 6: Toxic index yearly distribution within public and private firm

Appendix

fluid and specialist addictives		
Oil and gas service companies design fracturing fluids to create fractures and transport sand or other granular substances to prop open the fractures		
Type	Purpose	matched
Water-based Fluids		water friction reducing agent
		water gelling agent
Foam-based Fluids		defoamer
		antifoam agent
Oil-based Fluids		base oil
Emulsioin-based Fluids		emulsion preventer
		demulsifier
		nonemulsif
other Fluid		base fluid
addictives		
Additives are chemicals added to the fracturing fluid to achieve specific target properties of the fracturing fluid and constitute between 0.1 and 0.5% v/v of the total fracture fluid (Arthur et al., 2008; Holloway and Rudd, 2013; Spellman, 2013; Uddameri et al., 2016).		
Type	Purpose	matched
enhance fracture creation		
Fluid-Loss Additives	Fluid-loss additives are used to restrict leak-off of the fracturing fluid into the exposed rock at the fracture face, which leads to prevention of excessive leak-off, thereby maintaining fracturing fluid effectiveness.	fluid-Loss additives
Viscosifier		viscosifier
Temperature stabilizer		low temperature fiber
PH Control	Control the pH of the fluid	ph
		buffer
reduce formation damage		
Gel Breakers	minimize return of proppant and maximize return of fracturing fluid to the surface	gel breaker
		activator
Bactericides/Biocides	Fracture fluids typically contain gels that are organic and can therefore provide a medium for bacterial growth. Bacteria can break down the gelling agent reducing its viscosity and ability to carry proppant. Biocides are added to the mixing tanks with the gelling agents to kill these bacteria	bactericide
		bactericide myacide
		biocide
Surfactants		nonionic surfactant
		flowback surfactant
		surfactant
Clay Stabilizers	Clay stabilizers reduce clay swelling and function through ion exchange,	clay control
		kcl substitute
		clay stabilizer
Friction Reducers	Minimizes friction allowing fracture fluids to be injected at optimum rates and pressures	friction reducer
others		
Cross-linking agent	There are two basic types of gels that are used in fracturing fluids; linear and cross-linked gels. Cross-linked gels have the advantage of higher viscosities that do not break down quickly	crosslinker
Scale inhibitor	Control the precipitation of certain carbonate and sulfate minerals	scale inhibitor
		scale preventer
Iron control/stabilizing agent	Inhibit precipitation of iron compounds by keeping them in a soluble form	iron control
		iron reducing agent
Corrosion inhibitor	Used in fracture fluids that contain acids; inhibits the corrosion of steel tubing, well casings, tools, and tanks	corrosion inhibitor
		inhibitor aid
Wetting agent	Wetting agents are added to the desalter to help capture excess solids in the water, rather than allowing the undesired solids to travel further downstream into the process.	wetting agent
Acid Corrosion Inhibitors	Used in fracture fluids that contain acids; inhibits the corrosion of steel tubing, well casings, tools, and tanks	acid corrosion inhibitor
Breaker	Chemicals that are typically introduced toward the later sequences of a fracturing project to break down the viscosity of the gelling agent to better release the proppant from the fluid as well as enhance the recovery or "flowback" of the fracturing fluid	breaker
		breaker aid
Acid	To direct acid to the low-permeability section of a formation	diverter
		diverting agent
	For the fracturing of shale formations, acids are used to clean cement from casing perforations and drilling mud clogging natural formation porosity, if any prior to fracturing fluid injection (dilute acid concentrations are typically on the order of 15% v/v acid)	acid
Lubricant	Typically, the well is drilled by a rotary drill that uses a heavy mud (drilling mud) as a lubricant and as a means of producing a confining pressure against the formation face in the borehole, preventing blowouts.	lubricating agent
Viscosity Stabilizers	Viscosity stabilizers are added to the fracturing fluids to reduce the loss of viscosity at high reservoir temperatures	viscosity friction reducer
Gelling agents	Thicken the water-based solution to help transport the proppant material	gel
		gelling agent
Other Types Addictives		additive
		solvent
		stabiliz
		lubricating agent
		scavenger
		initiator
		clean perforation
		chelating agent
proppants		
Prevent and keep an induced hydraulic fracture open dur-ing and after a fracturing treatment so that the fracture does not collapse and close		
Type	Purpose	matched
Silica Sand		mesh sand/ sand
		fracturing sand
Resin-Coated Proppant		resin coated proppant
Manufactured Ceramic Materials		ceramic
Other Types Proppants		propp
		carrier

Figure A1: Chemical Purpose Explaination

Detailed Purpose Type	Purpose Matching Word	General Purpose Type
Water-based Fluids	water friction reducing agent	fluid and specialist addictives
Water-based Fluids	water gelling agent	fluid and specialist addictives
Foam-based Fluids	defoamer	fluid and specialist addictives
Foam-based Fluids	antifoam agent	fluid and specialist addictives
Oil-based Fluids	base oil	fluid and specialist addictives
Emulsioin-based Fluids	emulsion preventer	fluid and specialist addictives
Emulsioin-based Fluids	demulsifier	fluid and specialist addictives
Emulsioin-based Fluids	nonemulsif	fluid and specialist addictives
Other fluid	carrier	fluid and specialist addictives
Other fluid	base fluid	fluid and specialist addictives
Fluid-Loss Additives	fluid loss Additives	addictives enhance fracture creation
Viscosifier	viscosifier	addictives enhance fracture creation
Temperature stabilizer	low temperature fiber	addictives enhance fracture creation
PH Control	ph	addictives enhance fracture creation
Buffer	buffer	addictives enhance fracture creation
Gel Breakers	gel breaker	addictives reduce formation damage
Gel Breakers	activator	addictives reduce formation damage
Bactericides/Biocides	bactericide	addictives reduce formation damage
Bactericides/Biocides	bactericide myacide	addictives reduce formation damage
Bactericides/Biocides	biocide	addictives reduce formation damage
Bactericides/Biocides	microbiocide	addictives reduce formation damage
Bactericides/Biocides	antibacterial agent	addictives reduce formation damage
Bactericides/Biocides	antimicrobial	addictives reduce formation damage
Surfactants	nonionic surfactant	addictives reduce formation damage
Surfactants	flowback surfactant	addictives reduce formation damage
Surfactants	surfactant	addictives reduce formation damage
Clay Stabilizers	clay control	addictives reduce formation damage
Clay Stabilizers	kcl substitute	addictives reduce formation damage
Clay Stabilizers	clay stabilizer	addictives reduce formation damage
Friction Reducers	friction reducer	addictives reduce formation damage
Cross-linking agent	crosslinker	addictives
Scale inhibitor	scale inhibitor	addictives
Scale inhibitor	scale preventer	addictives
Iron control/stabilizing agent	iron control	addictives
Iron control/stabilizing agent	iron reducing agent	addictives
Corrosion inhibitor	corrosion inhibitor	addictives
Corrosion inhibitor	inhibitor aid	addictives
Wetting agent	wetting agent	addictives
Acid Corrosion Inhibitors	acid corrosion inhibitor	addictives
Breaker	breaker	addictives
Breaker	breaker aid	addictives
Acid	diverter	addictives
Acid	diverting agent	addictives
Acid	acid	addictives
Lubricant	lubricating agent	addictives
Viscosity Stabilizers	viscosity friction reducer	addictives
Gelling agents	gel	addictives
Gelling agents	gelling agent	addictives
Other Types Addictives	additive	addictives
Other Types Addictives	solvent	addictives
Other Types Addictives	stabilizer	addictives
Other Types Addictives	lubricating agent	addictives
Other Types Addictives	scavenger	addictives
Other Types Addictives	initiator	addictives
Other Types Addictives	clean perforation	addictives
Other Types Addictives	chelating agent	addictives
Silica Sand	mesh sand/ sand	proppants
Silica Sand	fracturing sand	proppants
Resin-Coated Proppant	resin coated proppant	proppants
Manufactured Ceramic Materials	ceramic	proppants
Other Types Proppants	propp	proppants

Figure A2: Purpose Matching Word

Appendix A.3: Legislation

1. 1969 National Environmental Policy act. (NEPA) 2. Safe Drinking Water Act (SDWA). - may have constraints of the underground fluid exploitation. 3. Clean Air Act 4. Clean water act 5. Toxic Substances Control Act The regulation of the discharge of toxic or hazardous substances into specific environments requires companies to fulfill their reporting obligations when the discharge of pollutants reaches a certain standard so that the public can be informed, and both government agencies and the public can monitor shale gas development. State level legislation: Each state in the U.S. has set strict boundaries on water withdrawal for shale gas development to prevent water waste and pollution. For example, St. Louisiana limits the scope of water withdrawal, New York requires that water withdrawal must be evaluated and licensed by the local regulatory agency, and Michigan has established a water withdrawal evaluation system to ensure that production and life are not affected by the use of water for shale gas development.

Appendix A4: Bartik IV

So far in this paper, we have not find a clean setting to get a casual relationship between financial constraints and firm pollutions. We use lagged one year financial to regress with well level pollution index and find that firm leverage are positively correlated with toxic usage. An Bartik IV that correlated with firm leverage but don't impact firm financial decisions would help. What we try is that us oil reserve amount yearly volatility, oecd production amount volatility and brent oil price yearly volatiliy are possible measures, we weighted these measures by the average first two year well shares (2012, 2013), find that these are weak ivs which may bring estimation bias.

Appendix A5: Green Transition - intensive and extensive

We further examined the R&D investment behavior of shale oil firms and found that only a small subset actively invests in research and development. Over the observed time period, R&D data is available for only seven firms. Among these firms, our analysis reveals that higher R&D expenditures—lagged by two years—are associated with reduced chemical usage in operations. This suggests that investment in innovation may contribute to more environmentally friendly extraction practices.

Appendix A6: Production Halt and Hedging

A very interesting statistical result is that after 2015, a certain amount of firms exits the shale industry or decrease their new well exploitations. From state level statistic, several states halted new exploitation, other special cases like west virginia, only provide data after 2019.

possible cause of green transition

Technological process policy tightness socio-economic environment stake holders' pressure

Appendix Financial ratios

The **Altman Z-score** is a financial metric used to assess a firm's likelihood of bankruptcy. It is calculated as a weighted sum of several financial ratios and is particularly useful for evaluating manufacturing firms. The formula is given by:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \tag{11}$$

where:

- $X_1 = \frac{\text{Working Capital}}{\text{Total Assets}}$ (Liquidity)
- $X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$ (Profitability)
- $X_3 = \frac{\text{EBIT}}{\text{Total Assets}}$ (Earnings Power)
- $X_4 = \frac{\text{Market Value of Equity}}{\text{Total Liabilities}}$ (Leverage)
- $X_5 = \frac{\text{Sales}}{\text{Total Assets}}$ (Efficiency)

The interpretation of the Z-score is as follows:

- $Z > 2.99$: The firm is in a **safe zone** (low risk of bankruptcy).

- $1.81 < Z < 2.99$: The firm is in a **gray zone** (moderate risk).
- $Z < 1.81$: The firm is in a **distress zone** (high risk of bankruptcy).
- A vague DID model may cut off reverse causality
- blueprint out the chemical index based on geolocation, see the effect
- How to build a exit model for the firms that exits the shale oil industry after paris agreement, will there be some new joining in?
- The syndicating loan data should be at least at bank level
- The new debt issuance data may changes the solution, need a more detailed information.
- Add descriptive statistics into the model
- A systematic evaluation of chemicals in hydraulic fracturing fluids and wastewater for reproductive and developmental toxicity. see the paper
- outcomes of the halliburton loophole: chemicals regulated by the safe drinking water act in the us fracking xxx