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 faced significant refinancing challenges, reflected in reduced bond issuance, weaker new bank lending, declining credit ratings, and higher costs of debt. Using a novel well-level index of toxic chemical usage combined with firm-level financial data, we employ a difference-in-differences–like approach to show that highly indebted firms significantly reduced their use of toxic chemicals by 52.5% following the policy shock. Empirically, we find that after the Paris Agreement, tighter financing conditions and heightened reputational concerns led firms to curb toxic-intensive operations. These findings highlight how climate commitments can influence environmental outcomes through financially induced pressure.

Keywords: Shale Oil, Paris Agreement, Debt Financing, Financial Frictions, Toxic Pollution Control.

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

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1 Introduction

The shale oil industry, which expanded rapidly after 2009, has become a dominant force in global oil production, accounting for more than half of total output. However, the hydraulic fracturing (fracking) techniques used in shale extraction have raised serious environmental concerns, including groundwater contamination from high salinity and non-biodegradable compounds, as well as the release of greenhouse gases. In response to growing environmental, social, and governance (ESG) awareness among policymakers and investors, shale producers have faced increasing pressure to adopt cleaner production practices. One such approach involves using more environmentally friendly proppants in hydraulic fracturing. The growing transparency provided by FracFocus, a public registry disclosing detailed well-level information across 12 U.S. states, allows us to track the adoption of cleaner production practices before and after the Paris Agreement.

This paper investigates whether firms' access to external financing shapes their environmental transition. The relationship is ambiguous. On the one hand, firms with better access to capital may have greater flexibility to invest in cleaner technologies. On the other hand, limited funding can constrain such investments. Yet, financial frictions—when combined with external pressure—can also influence firms' production and governance decisions, suggesting that climate policy shocks may operate through financially induced reputational mechanisms.

To examine this mechanism, we exploit the Paris Agreement as an exogenous shock that tightened financing conditions for carbon-intensive industries. We focus on firms' reliance on short-term debt to capture heterogeneity in refinancing risk prior to the Agreement. Following 2015, highly leveraged firms experienced pronounced refinancing challenges: higher debt costs, reduced bond issuance, and lower inflows of new syndicated loans. Contrary to the notion that financial constraints exacerbate pollution, we find the opposite—high short-term debt firms significantly reduced their use of toxic chemicals by about 52.5% (–0.75 log points) relative to less-levered peers. Importantly, this pollution reduction was not accompanied by higher production efficiency, implying that cleaner production arose from financing and reputational pressures rather than technological improvements.

Our channel analysis reveals that the link between financial constraints and pollution reduction operates primarily through external reputational pressure rather than internal governance or traditional financial channels. Financially constrained firms exposed to stronger media scrutiny curtailed toxic intensity more sharply, indicating that reputational concerns amplified the impact of financial frictions on environmental behavior. While some firms responded by strengthening internal oversight—such as establishing Environmental, Health, and Safety (EHS) committees—these actions do not appear to be the main drivers of pollution reduction. Similarly, we find no evidence that green institutional investors or banks played an active role in this process.

This study contributes to three strands of literature. First, it adds to the literature on the environmental impacts of hydraulic fracturing (HF). Prior studies, such as (Jackson et al., 2014), (Currie, Greenstone, & Meckel, 2017), and (Bonetti, Leuz, & Michelon, 2021), document the environmental risks of shale extraction, particularly groundwater contamination due to non-biodegradable chemicals ((Vidic, Brantley, Vandenbossche, Yoxtheimer, & Abad, 2013; Agarwal et al., 2020)). We complement this research by constructing a novel well-level toxic chemical usage index from FracFocus, enabling granular tracking of environmental behavior.

Second, we contribute to the literature on the effects of external policy shocks on firms' environmental decisions. Building on evidence from (Christensen, Hail, & Leuz, 2021) and (Kellogg, 2014), we show that the Paris Agreement, as a major global climate policy, intensified financing frictions for shale firms and induced cleaner production through reputational channels.

Third, we extend the debate on how financial constraints affect corporate environmental and social responsibility (CSR). While prior studies offer mixed evidence ((Cheng, Ioannou, & Serafeim, 2013; Attig, Cleary, El Ghoul, & Guedhami, 2013; Habib, Costa, Huang, Bhuiyan, & Sun, 2018; Chan, Chou, & Lo, 2017; Campbell, 2007)), we show that tighter financing constraints can promote cleaner production rather than deter it. The effect is strongest among firms under greater media scrutiny, highlighting that financial constraints can foster environmental improvement through reputational rather than financial or investor-driven channels.

Collectively, by integrating well-level environmental data with firm-level financial and ownership characteristics, our analysis reveals the financial and institutional conditions under which climate policy shocks effectively incentivize corporate environmental responsibility.

The remainder of the paper proceeds as follows. Section 2 provides background on hydraulic fracturing and environmental concerns. Section 3 describes the dataset. Section 4 analyzes the loan and debt market reaction. Section 5 presents firms' production responses. Section 6 investigates the transmission channels. Section 7 offers robustness tests, and Section 8 concludes.

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 is largely benefited from technology advances such as horizontal drilling, and hydraulic fracturing (HF). Operators adapt multiple chemicals for different purposes during fracturing. The fracturing process involves the injection of high-pressure "fracking fluid", normally consisting of water, sand and other proppants, into a borehole in order to induce fractures in deep-rock formations. Consequently, this facilitates the 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 alumina, maintain the fractures' openness (Von Estorff & Gandossi, 2015). Furthermore, chemical usage in HF works have effects on the productivity of wells, making the design of fracturing fluid for optimal performance based on the shale layer properties is of vital importance.

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

The potential hazards of HF fluids to health and the environment have 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 introductions of disclosure standards for HF wells and fracturing fluids also appears in several U.S. states. Since 2010, various state-level legislative 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 describes the construction of our dataset, which combines well-level hydraulic fracturing data from FracFocus with firm-level financial, credit, and ownership information. The well-level data provide detailed records of chemical usage, job start dates, and operational characteristics for hydraulic fracturing wells disclosures across 12 U.S. states. We match these data with firm-level financial information from Compustat, loan and bond transactions from Dealscan and Refinitiv SDC Platinum, and institutional ownership data from 13F filings. This integrated dataset allows us to quantify each well's toxic chemical intensity, measure firms' financial constraints based on short-term debt reliance, and examine how changes in financing conditions following the Paris Agreement affected firms' production and environmental 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 include initiated hydraulic fracturing date, well vertical distance, latitude and longitude geo-location, operators, federal land use, chemical purpose, chemical usage percentage in fracturing volumes, etc. We keep the sample after 2011. We drop the disclosures that (i) with no meaningful completion date (starting date is later than the ending date), (ii) erroneous 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 less than 80). (iii) For each year, we keep states with new exploitation wells larger than 5 for the estimation robustness. (iv) For 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 firms, voluntary disclosure and local legal forced disclosure are taken into consideration; (v)We keep wells with valid supplier information and operators with authentic financial data. In total, 18,961 disclosures are retained.

During the data selection process, we retain only firms and states with consistent time-series information. Firms that ceased production after the Paris Agreement, as well as states that introduced legislation halting shale production (such as New York State), are excluded from the sample. FracFocus provides basic information on well characteristics, which we use to control for drilling complexities. The data include variables such as vertical depth, horizontal length, and total water usage for each oil well. In addition, production processes, well complexity, and drilling profitability are related to the geographic location of wells. Wells located in different geological formations exhibit distinct physical properties. Finally, state-level policies are included as additional controls.

3.2 Chemicals Data

To evaluate the toxic information of the chemicals used during hydraulic fracturing, we first list all the unique chemicals identified with the Chemical Abstract Service identification number (CAS number) disclosed by FracFocus. CAS numbers, proposed by the CAS Registry, identify 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 for chemical information. A CAS number can be divided into three parts, with the first part having up to seven digits, the second part having two digits, and the third part a single digit as a check digit. Each part is connected by hyphens (format such as xxxxxxx-xx-x). We first drop FracFocus-disclosed CAS numbers that do not match the format, and then check whether the formatted CAS numbers exist or are valid. In total, 1,191 chemicals are defined as authentic. In spite of new chemicals, business secret products, or the lack of mandatory disclosure requirements from local governments, using CAS numbers we can find the Material Safety Data Sheet (MSDS) for chemicals, 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 disclosed by the ChemicalBook website. The Globally Harmonized System of Classification and Labelling of Chemicals (GHS) shown in the MSDS is a globally acknowledged benchmark overseen by the United Nations. Its purpose is to consolidate and replace the various hazardous substance categorisation and labelling methods previously employed worldwide. The standardized labels include: (i) Symbols or GHS hazard pictograms, including information on environmental concerns and human health hazards, which are assigned to multiple GHS hazard codes. The nine 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 1,191 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, such as Hazard statement(s) and Precautionary statement(s), is difficult to determine and therefore not taken into consideration. The GHS hazard pictograms allow us to explore toxic fluids' chemical properties within each subcategory, specifically from health and environmental hazard perspectives. The signal words provide the hazardous degree of each chemical. Based on this information, we are able to calculate the fluid toxicity index for each disclosure.

3.3 Firm-level Data

To address firm-level financial performance's impact on production decisions, we downloaded core financial characteristics of the publicly traded oil and gas firms in Compustat. As FracFocus received information from both publicly traded and private firms, we first use fuzzy matching to match FracFocus 'OperatorName' with Compustat 'conm'; we then manually identify the final list of publicly traded firms. Secondly, we set the Global Industry Classification Standard (GICS) code 'ggroup' to 1010.0 for selecting the energy industry. Thirdly, we keep public firms that have continued exploitation activity between 2012 and

2019.[1] We find 46 matching energy firms. Then we calculate the financial indicators used to determine financial constraints and for further corporate-level controls. Firm-level financial performance may be related to market leverage, Tobin's Q, other observable dimensions such as profitability, dividends, cash flow (in millions), and sales growth, etc. We use these financial variables as firm-level control variables. We also use firms' DEF 14A proxy statements to identify the presence of green board committees. Specifically, we capture both the intensive margin—the number of committee members involved in sustainability-related responsibilities—and the extensive margin—whether the firm has established a dedicated green or sustainability committee. In addition, we use data from PatentView to measure firms' green innovation activities. For shareholder information, we combine 13F filings with data from the Green Alliance list to identify institutional investors with environmental preferences and to measure the pressure from green shareholders.

3.4 Loan, Bond and Credit Data

We use the Dealscan database to evaluate overall loan market activity. We focus on loans with start dates between 2012 and 2019 and follow the data-cleaning process described in (Green & Vallee, 2024). We assign shares equally across banks for syndicated loans without detailed transaction amount information. We only focus on debt for general purposes rather than specific aims.[2] Among our selected firms, 2,485 deals are identified with loan properties such as loan terms, debt amount, new money injection, and spread. Properties like new money injection and spread are not available for each deal. We also use the Refinitiv SDC New Issues database to evaluate firm-level debt issuance activity. For the credit ratings, we use the Standard & Poor's (S&P) Long-Term Issuer Rating when available. For unobserved credit ratings, we double-check the credit information from Bloomberg.

[1] FracFocus was established in 2011, but state-level disclosure started in 2012. To make the time-series estimation more robust, we drop the first disclosure year.

[2] Debts with specific purposes include mergers, acquisitions, leveraged buyouts, exit financing, trade financing, IPO-related financing, and dividends or distributions to shareholders.

4 Loan and Bond Market 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 and toxic pollution. 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, funding availability, maturity structures, and ratings—reflect lenders' reassessment of long-term risks associated with brown-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 the syndicated loan and corporate debt markets to assess the extent to which financing conditions have tightened relative to firms with high short-term debt ratios for their intensive financing needs. Our analysis provides early evidence of how climate-related regulatory commitments affect firms' access to capital and potentially alter their production strategies.

4.1 Cost of Debt

To identify which shale firms are more affected, we divide them into two groups based on their firm-level debt structure. Our key measure is the short-term leverage ratio (ST_Debt), which captures a firm's reliance on short-term debt. 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 short-term debt usage patterns. Specifically, for each fiscal year up to 2015, 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 levels of 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. This balance-sheet-based indicator is consistent with the interpretation in (Rauh & Sufi, 2010), (Custódio, Ferreira, & Laureano, 2012), and (Harford, Klasa, & Maxwell, 2013), who document that a high share of short-term debt reflects limited access to long-term financing and greater exposure to refinancing risk. We argue that, under market tightening, these firms are more exposed to refinancing needs and therefore face greater lending frictions, such as higher debt costs, reduced access to funding, and declining credit ratings.

We first calculate each firm's pre-tax cost of debt as interest and related expenses divided by total debt. We find that after 2015, high-ST_Debt firms faced severe debt financing frictions. Figure 1 plots the average cost of debt for high- and low-ST_Debt firms over 2012–2020. Before 2015, cost trajectories were relatively stable and parallel across both groups. However, following 2015, high-ST_Debt firms experienced a significant rise in debt costs, surpassing low-ST_Debt 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:

$$CostofDebt_{j,t} = \alpha + \beta_1 \times Paris + \delta_j + \epsilon_{j,t} \tag{1}$$

where $CostofDebt_{j,t}$ is the cost of debt of operator j in year t. $Paris$ is the Paris Agreement dummy, and δ_j is the firm-level fixed effect. Table 6 reports the heterogeneity analysis of firm-level cost of debt after the Paris Agreement. Column (1) includes all firms with production information recorded in the year; the coefficient on the Paris dummy is positive and statistically significant at the 5% level, suggesting that, on average, shale oil 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 high-ST_Debt firms (Column 2), while the effect becomes statistically insignificant and economically smaller for 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 6 here]

4.2 Credit Ratings

Credit ratings provide a forward-looking measure of firms' downside risk, and green frictions may affect firms' creditworthiness. We use Standard and Poor's (S&P) Long-Term Issuer Rating for operator-level credit ratings. We then follow (Baghai, Servaes, & Tamayo, 2014) to linearize these ratings from 1 to 20. We use the following regression to test firms' credit rating changes under green frictions:

$$Credit_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \delta_j + \theta_t + \epsilon_{j,t} \tag{2}$$

where $Credit_{j,t}$ is the linearized credit rating of operator j in year t. $Paris$ is the Paris Agreement dummy, δ_j is the firm-level fixed effect, and θ_t is the year fixed effect. Figure 2 shows that credit ratings for both high- and low-short-term-leverage firms dropped notably in 2016. Regression results in Table 7 confirm this pattern. In Column (1), we find that the Paris dummy is negative and statistically significant, suggesting that shale oil firms, on average, experienced a 0.27-point decline in their credit ratings after the Agreement. In Column (2), however, the interaction term between Paris and short-term leverage is insignificant, implying that the downgrade was broad-based across the industry rather than concentrated among firms with higher short-term debt exposure.

[Insert Table 7 here]

4.3 Bond Issuance

We use the following regression to test the Paris Agreement's impact on high–short-term-debt-ratio firms' new debt issuance:

$$NewDebt_{i,j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{i,j,t} \tag{3}$$

where $NewDebt_{i,j,t}$ represents the properties of new debt i issued by firm j at time t, including the logarithm of debt amount and debt spread. $Paris$ is an indicator for years after the Paris Agreement, and $1\{\text{ST\_Debt}_j\}$ is a dummy for high–short-term-debt firms. $\delta_{j,t}$ are firm-level controls, γ_j is the firm fixed effect, and θ_t is the time fixed effect.

Regression results are shown in Table 8. 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 8 here]

4.4 Bank Loan and Green Bank

After the Paris Agreement, (Green & Vallee, 2024) finds that banks are divesting from the coal industry. Many NGOs have published lists of banks that are willing to exit the fossil fuel market by 2030. From the shareholders' perspective, stock holdings held by greener investors force fossil fuel firms to take green transitions. In this section, we discuss the actual loan market conditions for the shale oil industry after the Paris Agreement.

$$Loan_{i,j,l,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \lambda_{j,l} + \phi_t + \epsilon_{i,j,l,t} \tag{4}$$

where $Loan_{i,j,l,t}$ represents the properties of loan i borrowed by firm j from lender l at time t, including the logarithm of loan amount and loan spread. $Paris$ is an indicator of whether the debt is issued after the Paris Agreement; $1\{\text{ST\_Debt}_j\}$ is a dummy for high–short-term-debt firms; $\lambda_{j,l}$ is the borrower–lender fixed effect; and ϕ_t is the year fixed effect.

Results in Table 9, Panel A, show that, relative to other firms, high–short-term-debt firms' total new loan amounts did not change materially (Column 2), while the amount of new money raised from banks 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 banks' new money injections rather than on the price of credit.

We also follow (Kacperczyk & Peydró, 2022) to examine green banks' lending pressure on shale oil firms. Our green banks are labeled as Science-Based Targets initiative (SBTi) commitment banks. We label loans issued by green banks after their announcement dates with a dummy variable $GreenBank_i$. We then re-estimate a staggered difference-in-differences specification as follows:

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

Results in Table 9, Panel B, show that for firms with high short-term debt ratios, green banks reduce new money injections, while there is no significant heterogeneity in total debt amounts or spreads. When focusing on the main effect of green banks, the coefficients indicate that after the establishment of SBTi-related committees, green banks decrease their overall debt exposure but charge a higher spread. Our findings are consistent with (Kacperczyk & Peydró, 2021), who document that green banks reduce loan supply to polluting firms while imposing higher financing costs.

The apparent divergence, lower total loan amounts but higher new money injections, reflects a reallocation across borrowers. While financially constrained firms are not necessarily more polluting, green banks may perceive them as riskier counterparties in the post-Paris context. Lacking perfect information about firms' pollution exposure, green banks could use financial resilience (e.g., short-term leverage) as a proxy for transition risk. Consequently, they reduce exposures to firms with weaker balance sheets.

[Insert Table 9 here]

5 Firm Response

This section examines how shale oil firms adjusted their production behavior in response to the Paris Agreement. We analyze whether tighter financing conditions led financially constrained firms to modify their drilling activities and chemical usage, revealing how green policy shocks translate into real production adjustments.

5.1 Main Result – Pollution Control

To measure toxic chemical usage for each well, we propose a toxic index for each well i:

$$Toxic\_Index_{i,t} = \sum_{j} \left(PercentHFJob_{i,j,t} \times 1_{\{j \in \text{toxic}\}} \right) \tag{6}$$

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 an indicator function, which equals 1 if chemical j is labeled with the "Danger" signal word and 0 otherwise. Chemicals defined as dangerous but not environmentally hazardous—such as crystalline silica (SiO_2)—are excluded from the calculation.[3]

To address the right skewness of the chemical index, we follow the approach outlined by (Fetter, 2022). First, 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.

Appendix Figure A3 shows the yearly distribution of the well-level toxic index. We find a general decreasing trend in well-level toxic chemical usage. The lower percentiles decrease after 2015, while the upper percentiles decline from 2015 to 2018 but revert to previous levels thereafter.

We then examine well-level pollution heterogeneity between high–short-term-debt firms and others using the following equations:

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

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

where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage by well i operated by firm j in state s during year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable indicating whether a firm is highly reliant on short-term debt. $\delta_{j,t}$ are firm-level controls at year t; θ_i are well-level

[3] For chemicals labeled with the signal word "Danger," we further investigate their GHS classifications. We mainly find that silicon-related chemicals are less harmful to both the environment and human health. See: Global Silicones Council. Other chemicals such as Ca_2O_3 or NO_x compounds are more likely to be water-soluble or associated with aquatic impacts (e.g., toxicity to fish).

controls; $\gamma_{j,s}$ are operator–supplier fixed effects; λ_g are state fixed effects; and ϕ_t is the year fixed effect.

Regression results are shown in Table 10. 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 52.5% in toxic chemical usage.

Our results differ from those of (Bellon & Boualam, 2024), who study the pollution behavior of shale firms under financial distress, measured by default probabilities and Chapter 11 filings. They find that pollution intensity increases with financial distress. We reconcile this difference as follows. Our measure of financial constraints captures firms' structural dependence on short-term debt rather than proximity to bankruptcy. In this context, risk-shifting or last-resort behaviors are less relevant. In contrast, our identification relies on policy-induced frictions following the Paris Agreement, where lenders reassess environmental and refinancing risks. Without such policy pressure, financially constrained firms would have no incentive to voluntarily transition.

[Insert Table 10 here]

5.2 Selective Halt New Production

We examine whether financially constrained firms are more likely to cut back on new well exploitation. (Kellogg, 2014) shows that under oil price and consumption uncertainty, drilling activity declines as firms delay investment. Similarly, (GILJE, LOUTSKINA, & MURPHY, 2020) find that during periods of credit tightness or oil market shocks such as contango, highly leveraged oil firms reduce new production and scale back investment. Given that oil firms are typically highly indebted and capital-intensive, limited access to external financing is expected to have a significant impact on their drilling decisions.

Motivated by this literature, we test whether firms with persistently high short-term leverage—those facing stronger refinancing needs—respond to the Paris Agreement by cutting back new well drilling. Specifically, we compute firm-year measures of new well exploitation and estimate the following regression model:

$$NewWell_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{j,t} \tag{9}$$

where $NewWell_{j,t}$ is the logarithm of the number of new wells drilled by firm j in year t, $Paris$ is an indicator for years after the Paris Agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy for high–short-term-debt firms, γ_j are firm fixed effects, and θ_t are year fixed effects.

We first assess the overall industry response to the Paris Agreement by regressing drilling activity on a post-Paris dummy. In Table 11, the results are statistically insignificant, suggesting no average effect across all firms. We then focus on financial heterogeneity by interacting the Paris dummy with a time-invariant indicator of persistent short-term debt reliance. Our preferred specification includes both firm and year fixed effects to absorb time-invariant firm traits and common temporal shocks. The coefficient on the interaction term is negative and statistically significant, indicating that financially constrained firms reduced drilling activity more sharply after the Agreement. Our results are consistent with existing literature suggesting that firms facing financial uncertainty tend to halt or scale back production activities. Firms strategically selected greener new well exploitation when facing financial constraints.

[Insert Table 11 here]

5.3 No Green Productivity Premium

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

$$Production_{i,j,s,t} = \alpha + \beta_1 \times Toxic\_Index_{i,j,s,t} + \gamma_t + \theta_j + \delta_s + \epsilon_{i,j,s,t} \tag{10}$$

where $Production_{i,j,s,t}$ is the logarithm of average gas (or oil) production over period t, standardized by perforated footage, with $t \in \{6 \text{ months}, 12 \text{ months}\}$. $Toxic\_Index_{i,j,s,t}$ is the percentage of toxic chemical usage for well i operated by firm j in geolocation s at time t. γ_t are year fixed effects, θ_j are firm fixed effects, and δ_s are geolocation-grid fixed effects, where geolocation grids are defined by 1×1 degree changes in latitude and longitude.

Regression results presented in Table 12, 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 advantage.

[Insert Table 12 here]

6 The Channels

This section investigates the mechanisms through which financial frictions induced by the Paris Agreement affected firms' environmental behavior. We distinguish between internal governance responses—such as the establishment of Environmental, Health, and Safety (EHS) committees—and external reputational pressures from media scrutiny and public attention. While internal adjustments may reflect firms' alignment with evolving environmental expectations, reputational discipline appears to be the dominant force shaping pollution reduction.

6.1 Media Coverage Pressure

In the context of our study, high–short-term-debt (ST) firms may adjust their pollution behavior not solely due to direct compliance costs but also to mitigate potential reputational losses from media coverage 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.

We use the Reputation Risk Index (RRI) from RepRisk, available through the WRDS platform. The RRI aggregates firm-level exposure to reputational risks across a wide range of ESG issues. The index is constructed by systematically monitoring international and local media outlets, blogs, newsletters, NGO reports, and government releases in multiple languages, identifying adverse events such as environmental incidents, governance controversies, and public protests.

Each company's RRI score (ranging from 0 to 100) is driven by the frequency and reach of news items, the severity and novelty of incidents, and the firm's prior exposure: firms with little prior negative attention tend to experience greater score jumps when newly criticized. Instead of using the RRI score itself, we focus on its annual trend (ΔRRI), which captures the change in a firm's reputational exposure over time. This dynamic measure better reflects shifts in media scrutiny—a rising trend ($\Delta RRI > 0$) signals intensifying public pressure, whereas a declining trend ($\Delta RRI < 0$) suggests easing reputational concerns.

We use both the interaction term and subsample regressions to test the media coverage pressure channel (Table 13). In Column (1), the interaction between $Paris \times ST\_Debt$ and media pressure (ΔRRI) shows a negative coefficient, suggesting that financially constrained shale firms facing stronger increases in negative media attention are more likely to reduce the intensity of toxic chemical use after the Paris Agreement. This effect remains significant in the high-pressure subsample (Column 3) but disappears when $\Delta RRI < 0$ (Column 4), indicating that reputational shocks primarily constrain firms under rising media scrutiny.

Our analysis builds on a growing literature showing that fluctuations in media coverage materially affect firms' behavior through external monitoring and information channels. For example, (Heese, Pérez-Cavazos, & Peter, 2021) show that local newspaper closures reduce media scrutiny and increase facility-level misconduct, while (Gao, Lee, & Murphy, 2019) demonstrate that newspaper closures raise borrowing costs for municipal issuers by weakening public oversight. In contrast to these studies, which examine reductions in media coverage, we focus on how intensified ESG media scrutiny influences financially constrained firms' green transition behavior.

[Insert Table 13 here]

6.2 Green Shareholders Engagement

Although firms' adoption of environmentally sustainable practices is central to addressing climate change, managers often display a "business-as-usual" attitude and remain reluctant to alter their environmental strategies. To overcome this inertia, institutional investors have increasingly joined forces through coalitions that engage firms on climate issues.

We obtain institutional ownership data from the WRDS 13F Holdings database, which records equity holdings of large institutional investors in U.S. public firms. Following standard practice, we aggregate quarterly observations to the annual level and compute annual percentage ownership by investors affiliated with different "green alliances." Specifically, we focus on three major coalitions of climate-oriented investors:

1. Net Zero Asset Owner/Manager Alliance (NZAM): A coalition of large pension funds, insurance companies, and asset managers that have committed to aligning their portfolios with net-zero greenhouse gas emissions by 2050. Members pledge to gradually decarbonize their assets and increase investments in sustainable activities.

2. Climate Action 100+ (CA100+): A network of global asset managers, asset owners, and service providers engaging with the world's largest corporate greenhouse gas emitters. The main channel of influence is active shareholder engagement, including filing shareholder proposals, voting, and direct dialogue with corporate boards.

3. Global Fossil Fuel Divestment Database (GFFD): A record of universities, foundations, endowments, religious organizations, and public pension funds that have publicly committed to divesting from coal, oil, and gas companies. The pressure here is mainly reputational, as divestment announcements generate media coverage and alter public perceptions of targeted firms.

We manually identified green shareholders from 13F filings and linked them to the above alliances. For each firm-year, we aggregated the ownership shares held by alliance-affiliated investors. We then examine two questions: (1) whether green shareholders reduced their holdings in fossil fuel firms after the Paris Agreement; and (2) whether a higher percentage of green ownership is associated with more environmentally friendly firm behavior, such as reduced toxic chemical usage and increased green innovation.

The estimation results are presented in Tables 14 and 15. We find no significant reduction in institutional ownership among highly leveraged firms following the Paris Agreement. This suggests that large climate-oriented investors did not immediately divest from financially constrained fossil fuel firms. Next, we interact the post-Paris indicator with a dummy for green institutional ownership. Table 15 shows that high green ownership is not associated with a stronger decline in toxic chemical usage. The insignificant interaction term indicates that the presence of green investors did not amplify the environmental response of debt-constrained firms.

Overall, these findings imply that shareholder engagement did not serve as an active channel of transition in this context. Consistent with (Krueger, Sautner, & Starks, 2019), ESG-oriented investors appear to focus primarily on risk management and long-term engagement, rather than exerting short-term pressure or enforcing immediate pollution reduction.

[Insert Table 14 here]

[Insert Table 15 here]

6.3 Internal Moderation of Green Governance

To further explore the mechanism, we examine the role of internal governance as a moderating factor of the green pressure channel. While shareholder pressure represents an external source of green expectations, internal governance determines whether firms are capable of translating these external pressures into strategic or operational adjustments. (Albuquerque, Koskinen, & Zhang, 2018) show both theoretical and empirical evidence that corporate social responsibility (CSR) activities decrease systematic risk and increase firm value.

Our measure of green governance is constructed from manually collected information in firms' DEF-14A proxy statements. Specifically, we identify whether a firm has established a dedicated Environmental, Health, and Safety (EHS) committee at the board level. We code a dummy variable, *Green Board*, equal to one if the proxy statement in a given year provides detailed information about the EHS committee. In addition, we record the number of directors serving on this committee to capture the intensity of board-level engagement in environmental governance.

EHS committees represent a formal governance mechanism through which boards oversee firms' exposure to environmental risks, workplace safety standards, and compliance with environmental regulations. Prior literature in corporate governance suggests that such committees can influence firms' disclosure quality, environmental performance, and long-term risk management by integrating sustainability considerations into strategic decision-making.

The measure of green innovation is constructed at the firm level using patent data from PatentView. We identify green patents by retaining only those patents classified under the Y02 scheme of the European Patent Office's Cooperative Patent Classification (CPC). Following the literature, patents serve as a proxy for innovative activity, and the Y02 tagging specifically captures innovations related to the green transition, such as renewable energy technologies, improvements in energy efficiency, and carbon mitigation strategies. This approach, widely adopted in empirical studies (Angelucci, Hurtado-Albir, & Volpe, 2018), provides a consistent and internationally comparable standard for measuring firm-level green innovation.

We use the following model to estimate firms' internal green governance and green innovation:

$$Green_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{j,t} \tag{11}$$

where $Green_{j,t}$ represents firm j's green attributes at time t, including (i) the logarithm of green patents labeled under the CPC Y02 classification, (ii) a dummy indicating whether the firm has a green board in year t, and (iii) the logarithm of the number of green board members. $Paris$ is an indicator for years after the Paris Agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy for high–short-term-debt firms, γ_j are firm fixed effects when included, and θ_t are year fixed effects.

For the *Green Board* variable, we also provide Probit regression estimates and corresponding average marginal effects of $Paris \times ST\_Debt$.

Regression results are presented in Table 16. The coefficient on the interaction term $Paris \times ST\_Debt$ is positive and statistically significant for both the Green Board dummy and the number of green committee members, indicating that firms with high reliance on short-term debt were more likely to respond to post-Paris green pressures by establishing green-related governance structures. Specifically, Column (2) shows that the probability of having a green board significantly increases for these financially constrained firms, and Column (3) reveals a higher count of green committee members. We do not observe similar results for green innovation.

Moreover, the Probit regression and marginal effect results in Table 17 confirm this pattern. In the specification without controls, the interaction term $Paris \times ST\_Debt$ has a coefficient of 0.931, with an average marginal effect of 0.314, suggesting that high–ST_Debt firms are 31.4 percentage points more likely to establish a green board after the Paris Agreement. Even after including financial controls such as firm size, profitability, and investment ratios, the effect remains positive and significant, with a marginal effect of 16.5 percentage points.

Our findings suggest that the Paris Agreement introduced new pressures for firms with higher short-term debt reliance, leading to greener governance responses. The observed increase in green board formation and committee participation among these firms indicates that financially constrained firms may be more responsive to climate regulation or investor pressure, possibly as a strategic adaptation to maintain financing access or improve perceived ESG performance.

[Insert Table 16 here]

[Insert Table 17 here]

7 Robustness and Alternative Explanations

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) as if the treatment started in that year, and zero otherwise. We then estimate the same baseline specification:

$$Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Shock + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t} \quad (12)$$

where $Toxic\_Index_{i,j,s,g,t}$ is the percentage of toxic chemical usage for well i operated by firm j in state s during year t. $1\{\text{ST\_Debt}_j\}$ is a dummy variable equal to one if firm j relies heavily on short-term debt. $Shock$ is a dummy variable representing a randomly assigned placebo shock year before or after the Paris Agreement. $\delta_{j,t}$ are firm-level controls at year t; θ_i are well-level controls; $\gamma_{j,s}$ are operator–supplier fixed effects; λ_g are state fixed effects; and ϕ_t are year fixed effects.

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 4 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 any strong systematic pre-trends. 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 behavior, particularly for those with higher short-term debt exposure.

7.2 Oil Price Shock Mechanism

One major concern in our analysis is that the global oil market experienced significant turbulence during the Paris Agreement period. In mid-2014, oil prices experienced a historic collapse, with WTI crude plummeting from over \$100 per barrel to below \$50 by the end of the year. The sharp decline was driven by a combination of rising U.S. shale oil production, OPEC's refusal to cut output, and weakening global demand. The crash had far-reaching impacts on oil-producing firms, financial markets, and energy policy worldwide.

In the main regression, we control for *Oil_beta*, which measures a firm's stock price sensitivity to WTI oil prices. *Oil_beta* is widely used in the climate finance literature (see (Ilhan, Sautner, & Vilkov, 2020); (Ginglinger & Moreau, 2023)). In this section, we more directly test the oil price mechanism. (Shi & Zhang, 2024) highlight a mechanism whereby oil prices serve as a primary driver of brown firms' "greenium." When oil prices fall, investor expectations regarding the fossil fuel industry deteriorate, raising the cost of capital for brown firms. This, in turn, affects firms' asset allocations and investment decisions. Motivated by this mechanism, we examine whether oil price shocks influence firms' environmental behavior.

However, oil prices are themselves endogenous, influenced by a variety of macroeconomic and geopolitical factors ((Kilian, 2009); (Baumeister & Hamilton, 2019)). Different types of oil shocks can impact the energy sector's growth prospects in heterogeneous ways, making it difficult to isolate causal effects. To address this issue, we follow (Känzig, 2021) and implement an instrumental-variable (IV) strategy that leverages OPEC announcement surprises as plausibly exogenous shocks to global oil supply.

Specifically, we estimate the following two-stage model using monthly WTI prices and OPEC surprise measures as instruments:

$$\Delta \log(\mathrm{WTI})_t = \gamma_0 + \gamma_1 \cdot \mathrm{OPEC}_t + u_t \tag{13}$$

$$\begin{aligned} Toxic\_Index_{i,j,s,g,t} = \beta_0 &+ \beta_1 \cdot \Delta \widehat{\log(\mathrm{WTI})}_t + \beta_2 \cdot \left(\Delta \widehat{\log(\mathrm{WTI})}_t \times 1\{\mathrm{ST\_Debt}_j\} \right) \\ &+ \beta_3 \cdot \left(\Delta \widehat{\log(\mathrm{WTI})}_t \times 1\{\mathrm{ST\_Debt}_j\} \times Paris \right) \\ &+ \beta_4 \cdot (Paris \times 1\{\mathrm{ST\_Debt}_j\}) + \theta_i + \varepsilon_{i,j,s,g,t} \end{aligned} \tag{14}$$

where OPEC_t denotes the surprise component of OPEC announcements, and $1\{\mathrm{ST\_Debt}_j\}$ is an indicator for firms with high short-term debt exposure. WTI denotes the monthly oil price.[4]

[4]Oil price data are from the U.S. Energy Information Administration, Cushing, OK WTI Spot Price FOB.

Panel A of Table 18 presents the first-stage results, which confirm that the instrument is strong: a one-unit oil supply shock increases the log return of WTI by 1.2437, with a first-stage F-statistic well above 10.

Panel B of Table 18 presents the second-stage regression results. The coefficient on the instrumented oil price return, $\Delta \widehat{\log(\mathrm{WTI})}$, is positive and statistically significant, indicating that increases in oil prices are associated with higher pollution levels. This pattern is consistent with firms expanding production when profitability improves. The triple interaction term $\Delta \widehat{\log(\mathrm{WTI})} \times ST\_Debt \times Paris$ reveals a nuanced mechanism: financially constrained firms tend to increase pollution more strongly when benefiting from oil price upswings, suggesting that improved cash flows weaken their incentives for green behavior. In contrast, the interaction between the Paris Agreement dummy and the high–short-term-debt dummy remains large and negative, consistent with our baseline difference-in-differences results. This implies that green policy constraints, such as the Paris Agreement, still exert a countervailing force, pushing financially constrained firms to reduce pollution despite favorable oil price conditions.

Our findings complement (Shi & Zhang, 2024), who show that fluctuations in oil prices significantly shape the cost of capital for energy firms and partially drive the observed "greenium" in financial markets. While their study emphasizes investor preferences and market-based green premia, our results demonstrate that oil price shocks also affect real firm behavior—specifically, pollution outcomes. In particular, financially constrained firms tend to increase pollution following oil price upswings, likely due to relaxed capital constraints. However, our difference-in-differences estimates also show that external green policies such as the Paris Agreement continue to exert disciplining effects, even during favorable commodity price cycles.

[Insert Table 18 here]

7.3 Alternative Financing Access

Our measure of short-term leverage is constructed from balance-sheet information, capturing all liabilities due within one fiscal year. A potential concern is that large and financially sound corporations—such as ExxonMobil or Chevron—often issue commercial paper as a convenient source of short-term funding for working capital purposes, rather than due to limited access to long-term debt markets. To ensure that our results are not driven by such unconstrained firms, we re-estimate the main regressions after sequentially excluding the largest 3, 6, and 8 firms by total assets. The results in Table 19 remain robust, suggesting that our findings are not mechanically driven by large firms with access to alternative short-term financing sources such as commercial paper.

[Insert Table 19 here]

7.4 Bank Lending Access

We test whether the post-Paris reduction in toxic intensity among debt-constrained firms is affected by the relaxation of financing constraints. Specifically, we interact the post-Paris dummy with an indicator for firms that received bank loans. If the decline in pollution primarily reflects financial tightening, the effect should be weaker among firms with access to bank financing. Table 20 reports the results.

The interaction term between the Paris Agreement dummy and the Bank Loan indicator is positive and statistically significant, indicating that the reduction in toxic intensity is substantially smaller for firms that obtained bank loans. In other words, financially constrained firms without new bank lending reduced pollution more sharply, whereas those with access to external credit mitigated their environmental response. We do not find evidence of additional pressure from green banks.

[Insert Table 20 here]

8 Concluding Remarks

This paper shows that global climate commitments can shape corporate environmental behavior through financial and reputational channels. Following the Paris Agreement, shale oil firms with heavier short-term debt reliance faced greater refinancing frictions—manifested in higher borrowing costs, reduced bond issuance, and tighter bank lending—which constrained their financial flexibility. Rather than worsening environmental outcomes, these pressures prompted a strategic adjustment: high short-term leveraged firms cut toxic chemical use by about 53 percent and scaled back new well drilling, signaling a strategically shift toward greener production choices.

Firms under stronger refinancing pressure were also more responsive to reputational risks. Greater media scrutiny intensified the disciplinary effect of financial constraints, reinforcing cleaner operational choices. In contrast, neither green investors nor banks appear to have actively directed capital toward cleaner firms, and internal governance changes such as the establishment of EHS committees remained largely symbolic.

Taken together, the evidence suggests that climate policy shocks operate not through active green capital reallocation, but through financially induced reputational pressure that tightens financing conditions and amplifies external monitoring. This mechanism highlights how global climate commitments can indirectly discipline indebted firms toward environmental improvement—even in the absence of explicit regulatory enforcement or investor activism.

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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 as firm control their detailed calculation methodology.

Financial indicators	**Calculation methods**
Dividened	Dividends - total divided by Total Asset
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
Cost of Debt	Interest and Related Expense (XINT) Divided by Debt
Market Capitalization	Equity price multiplied by shares outstanding, $prcc\_c \times csho$ in Compustat.
Market Leverage	Debt divided by the sum of Debt and Market Capitalization.
Log(Total Asset)	Natural logarithm of book asset (AT in Compustat)
Profit	EBITDA divided by total assets
Capex/Total Asset	Capital expenditures divided by total assets
Tangibility	Net property, plant, and equipment divided by total assets
Delta Sale	Annual percentage change in sales revenue for each firm.
Log(SGA/Sale)	Selling, General, and Administrative expenses divided by sales.
Oil Beta	Sensitivity of Monthly stock returns to monthly WTI oil returns. The variable is computed for each month with 5 years rolling window. Winsorized at 1% level.

Table 5: Summary Statistics of Variables

Firm Variable	Obs	Mean	Std. Dev.	Min	Max
Log Total Asset	300	9.166	1.940	3.569	12.846
Q	289	1.055	0.487	0.265	2.828
Capex/Total Asset	300	0.196	0.124	0.021	0.606
Profit	297	0.077	0.166	-0.476	0.407
Dividend	297	0.010	0.014	0.000	0.056
Tangibility	300	0.801	0.120	0.437	0.979
Log(SGA/Sale)	285	-10.094	2.739	-16.215	-0.933
Delta_Sale	296	0.150	0.610	-0.667	3.350
Wellcount	303	157.505	232.348	5	1642
Patent_count	303	4.525	16.414	0	115
Green_board	255	0.431	0.496	0	1
Committee_number	255	1.729	2.313	0	9
NetZero_shares	236	12.113	6.620	0	32.582
Climate100_shares	236	11.357	5.770	0	36.175
GFFD_shares	236	9.208	4.751	0	21.362
Well-level variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Toxic Index	18,961	-1.6364	1.1199	-12.4743	1.8320
Log Vertical Depth	18,961	9.0958	0.2936	0.0000	17.5370
Log Horizontal Length	18,961	8.8780	0.3876	2.1656	9.8452
Log Water	18,961	15.6204	0.8976	3.1781	19.1210

Table 6: Paris Agreement Impact on Firm Cost of Debt

We use the following empirical model to explore firm cost of debt heterogeneity. Cost of $\text{Debt}_{j,t} = \alpha + \beta_1 \times Paris + \delta_j + \epsilon_{j,t}$, where Cost of $\text{Debt}_{j,t}$ is the cost of debt of operator j in year t, calculated by interest and related expense divided by debt. $Paris$ is Paris agreement dummy, δ_j is firm level fixed effect. All regressions controls with firm characteristics from Compustat, financial variables including logarithm of total asset, profitability and market leverage. Column (1) conducted on the total sample, in columns (2) and (3) we conduct subgroup regression with short term leverage ratio properties before paris agreement. Standard errors are clustered at operator level and are given in parentheses. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Cost of Debt All	(2) Cost of Debt High ST	(3) Cost of Debt Low ST
Paris	0.00746**	0.00790*	0.00348
	(0.00326)	(0.00442)	(0.00360)
Log Total Asset	-0.01860***	-0.02269***	-0.01135*
	(0.00655)	(0.00812)	(0.00569)
Profit	-0.00391	-0.01451	0.00653
	(0.01380)	(0.02369)	(0.01388)
Market_Leverage	-0.00351	-0.01178	0.00491
	(0.01130)	(0.01763)	(0.01414)
Mean Dep.Var.	0.056	0.053	0.061
Obs.	258	166	92
R^2	0.509	0.490	0.602
Operator FE	Y	Y	Y

Table 7: Paris Agreement Impact on Firm Credit Rating

We use the following empirical model to explore firm credit rating. $Credit_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \delta_j + +\theta_t + \epsilon_{j,t}$, where $Credit_{j,t}$ is the linearized credit rating of operator j in year t. Credit data resourced from Standard and Poor's (S&P) LongTerm Issuer Rating. $Paris$ is the Paris Agreement dummy, δ_j is firm level fixed effect, θ_t is the year fixed effect. Column(1) estimates Paris Agreement's impact on shale oil firm's credit rating. Column(2) report estimation of Paris agreement's impact on high short-term leverage firms (ST-Firms). All regressions controls for firm financial like logarithm of total asset, profitability and market leverage (resource from Compustat), Oil_Beta controls for firm's stock price sensitivity to oil price. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Credit Rating	Credit Rating
Paris	-0.27412*	
	(0.14365)	
Paris$\times ST_Debt$		-0.20567
		(0.37340)
Log Total Asset	1.54902***	1.57062***
	(0.27286)	(0.28891)
Profit	0.10848	0.26771
	(0.65367)	(0.93033)
Market_Leverage	-0.65304	-1.08282*
	(0.55993)	(0.64140)
Oil_Beta	-4.70092	-8.03691
	(13.37685)	(12.33152)
Mean Dep.Var.	8.958	8.958
Obs.	263	263
R^2	0.980	0.981
Operator FE	Y	Y
Year FE		Y

Table 8: Paris Agreement and Debt Market Reactions: New Bond Issue

The table shows the the estimation of the following panel fixed effect regression: $NewDebt_{i,j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \delta_{j,t} + \gamma_j + \theta_t + \epsilon_{i,j,t}$ where $NewDebt_{i,j,t}$ is firm j's new debt i's properties at time t including Logarithm of Debt Amount, Debt spread, resourced from Refinitiv SDC new debt issue database. $Paris$ is an indicator of years after Paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term leverage ratio firms, $\delta_{j,t}$ is the firm controls, γ_j is firm fixed effect, θ_t is the time fixed effect. All regressions include control for logarithm of total asset, profitability, Market Leverage, Tobin's Q, Altman Z score, Sale to Total Asset, Interest Expense, all financial ratios resource from Compustat. Standard errors are clustered at year_month level and are given in parentheses. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Log(Amount)	Spread
Paris×ST_Debt	-0.34702**	0.86510**
	(0.15310)	(0.37734)
Log Total Asset	-0.00001**	-0.00002**
	(0.00000)	(0.00001)
Profit	-0.97298**	0.20955
	(0.45342)	(1.61418)
Market_Leverage	0.59241	1.61566
	(0.42406)	(1.42243)
Q	-0.16949	0.60064
	(0.18116)	(0.40083)
Z	0.07376	-0.28620
	(0.09381)	(0.20197)
Sale/Total Asset	0.06811	-1.31963***
	(0.17284)	(0.46310)
Interest Expense	-0.00033	0.19732
	(0.00239)	(0.21469)
Mean Dep.Var.	6.281	2.254
Obs.	367	217
R^2	0.768	0.829
Firm FE	Y	Y
Year FE	Y	Y

Table 9: Paris Agreement and Syndicated Loan Market Reactions

The table shows the estimation of the following panel fixed effect regression: In Panel A, $Loan_{i,j,l,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \lambda_{j,l} + \phi_t + \delta_p + \epsilon_{i,j,l,t}$ where $Loan_{i,j,l,t}$ is debt i's properties including, Logarithm of Loan Amount, Debt spread borrowed by oil firm j with lender l at time t resourced from Dealscan database. $Paris$ 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. In Panel B, $Loan_{i,j,l,t} = \alpha + \beta_1 \times GreenBank_i \times 1\{\text{ST\_Debt}_j\} + \lambda_{j,l} + \phi_t + \delta_p + \epsilon_{i,j,l,t}$ We estimate the staggered difference in differences specification with a label of whether loans issued by green banks after the announcement date. $*$, $**$, and $***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Paris Agreement Shock

	(1) Debt_amount	(2) New_money	(3) Spread
Paris×ST_Debt	0.01035	-1.19703***	-0.16113
	(0.03048)	(0.30561)	(0.12135)
Debt Term	0.01928***	0.12668*	-0.01692
	(0.00703)	(0.06605)	(0.02040)
Mean Dep.Var.	3.436	5.370	1.835
Obs.	2485	305	2247
R^2	0.966	0.878	0.679
Borrower-Lender FE	Y	Y	Y
Year FE	Y	Y	Y

Panel B: Green Bank Effects

	(1) Debt_amount	(2) New_money	(3) Spread
Green Bank×ST_Debt	-0.02447	-0.84311*	-0.11886
	(0.11920)	(0.48181)	(0.13603)
Green Bank	-0.06012***	1.36383***	0.22290*
	(0.01952)	(0.33089)	(0.11942)
Debt Term	0.01973***	0.14377**	-0.01884
	(0.00702)	(0.06802)	(0.02017)
Mean Dep.Var.	3.436	5.370	1.835
Obs.	2485	305	2247
R^2	0.966	0.873	0.678
Borrower-Lender FE	Y	Y	Y
Year FE	Y	Y	Y

Table 10: Firm Production Reaction: Pollution Control

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 depends more on short term debt financing. $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect for the controlling of firm's access of toxic chemicals. λ_g is state level fixed effect, ϕ_t is the year fixed effect. All regressions are controlled for well production properties such as logarithm of well vertical depth, logarithm of well horizontal length, logarithm of well water usage, well levels data are resourced from FracFocus. All regressions are also controls with firm level characteristics resourced from Compustat like logarithm of Total Asset, Tobin's Q, Capex to Total Asset, Profitability, Dividend Ratio, Tangibility, Operating Expense, Sale Percentage, and Oil Beta. Standard errors are clustered at operator level and are given in parentheses. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Toxic Index	(2) Toxic Index
2012×*ST_Debt*	0.00778	
	(0.66395)	
2013×*ST_Debt*	0.07942	
	(0.15504)	
2015×*ST_Debt*	-0.42910	
	(0.34260)	
2016×*ST_Debt*	-0.89623**	
	(0.37991)	
2017×*ST_Debt*	-0.91638**	
	(0.41552)	
2018×*ST_Debt*	-1.18407***	
	(0.43721)	
2019×*ST_Debt*	-1.50281*	
	(0.77512)	
Paris×*ST_Debt*		-0.74548***
		(0.22487)
Log True Vertical Depth	0.06115	0.05497
	(0.04726)	(0.04747)
Log Horizontal Length	0.14168**	0.14098**
	(0.05673)	(0.05713)
Log Water Volume	-0.21532***	-0.21626***
	(0.03955)	(0.03947)
Log(Total Asset)	-0.39727	-0.35971
	(0.29008)	(0.30222)
Q	-0.88382***	-0.93327***
	(0.31679)	(0.33440)
Capex/Total Asset	1.87239*	1.76976
	(1.03872)	(1.15634)
Profit	0.81216	0.51052
	(0.68223)	(0.58288)
Dividend/Total Asset	-12.29308	-21.39727
	(16.40122)	(18.60460)
Tangibility	-0.48914	-0.68219
	(1.27147)	(1.41295)
Log(SGA/Sale)	0.17279	0.06903
	(0.13297)	(0.11828)
Delta_Sale	0.06453	0.01520
	(0.19670)	(0.21421)
Oil_beta	-33.21436	-45.27810
	(59.46284)	(66.06001)
Mean Dep.Var.	-1.636	-1.636
Obs.	18961	18961
R^2	0.527	0.524
Year FE	Y	Y
Operator-supplier FE	Y	Y
Geo FE	Y	Y

Table 11: Firm's Production Reaction: New Well Exploitation

We use the following model to estimate firm's new well exploitation decision, $NewWell_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{j,t}$ where $NewWell_{i,j,t}$ is the logarithm of firm j's new number count at time t resourced from FracFocus database, $Paris$ is an indicator of years after Paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, γ_j is firm fixed effect, θ_t is the time fixed effect. Column (1) reports the estimation of Paris agreement impact on industry level production, Column (2) reports the production hetero under green policy. Standard error are given in parentheses and clustered at operator level. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	New Well	New Well
Paris	0.05844	
	(0.12642)	
Paris×ST_Debt		-0.49488**
		(0.23097)
Mean Dep.Var.	4.314	4.314
Obs.	301	301
R^2	0.672	0.840
Year FE		Y
Operator FE	Y	Y

Table 12: Green Well with Limited Production Benefits

The table shows the the estimation of the following panel fixed effect regression $Production_{i,j,s,t} = \alpha + \beta_1 \times Toxic\_Index_{i,j,s,t} + \gamma_t + \theta_j + \delta_s + \epsilon_{i,j,s,t}$ where $Production_{i,t}$ is the gross gas (oil) production within t period average standardized by perforated foot, $t \in \{6\text{ month}, 12\text{ months}\}$, Production data resourced from DrillingInfo. All regression controls for year fixed effect, firm fixed effect and 1*1 longitude to latitude fixed effect. All regression also controls for well drilling properties like logarithm of well depth, logarithm of well length, logarithm of water usage. All well level data resourced from FracFocus. Standard errors are clustered at operator level and given in parentheses. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	Log prod_6	Log prod_12
Toxic Index	-0.00054	0.00380
	(0.01158)	(0.01178)
Log True Vertical Depth	0.15417***	0.14237***
	(0.04843)	(0.04380)
Log Horizontal Length	-0.36636***	-0.31549***
	(0.04713)	(0.04796)
Log Water Volume	0.12571***	0.12233***
	(0.02585)	(0.02574)
Obs.	61115	61123
R^2	0.425	0.462
Year FE	Y	Y
Geo FE	Y	Y
Firm FE	Y	Y

Table 13: Media Coverage Pressure

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times \Delta RRI_{j,t,t-1} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ 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, $\Delta RRI_{j,t,t-1}$ is firm year level media coverage pressure, $\delta_{j,t}$ 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. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Toxic Index Interaction	(2) Toxic Index *All*	(3) Toxic Index $\Delta RRI > 0$	(4) Toxic Index $\Delta RRI < 0$
Paris$\times ST_Debt \times \Delta RRI$	-0.21085*			
	(0.10775)			
Paris$\times ST_Debt$	-0.73270***	-0.74548***	-0.81479**	0.06885
	(0.24940)	(0.22487)	(0.36394)	(0.34683)
ΔRRI	0.01152			
	(0.05613)			
Mean Dep.Var.	-1.636	-1.636	-1.664	-1.634
Obs.	16970	18961	10823	7268
R^2	0.534	0.524	0.549	0.618
Year FE	Y	Y	Y	Y
Operator-supplier FE	Y	Y	Y	Y
Geo FE	Y	Y	Y	Y
Well Control	Y	Y	Y	Y
Firm Control	Y	Y	Y	Y

Table 14: External Pressure: Green Investor Holdings

We use the following model to estimate firm's internal green governance, $Greenownerpct_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{j,t}$ where $Greenownerpct_{j,t}$ is firm j's green institutional ownership holding percentage at time t. Holding data resourced from 13F fillings, with labeling green institution holders under Net Zero Alliance, Climate 100 and Global Fossil Fuel Divestment Database. $Paris$ is an indicator of years after Paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, γ_j is firm fixed effect when needed, θ_t is the time fixed effect. $*, **, and***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
	NetZero	Climate100	GFFD
Paris×ST_Debt	-0.52129	-0.91979	-1.13830
	(1.53893)	(1.50325)	(1.13020)
Mean Dep.Var.	12.135	11.312	9.259
Obs.	232	232	232
R^2	0.798	0.784	0.786
Year FE	Y	Y	Y
Operator FE	Y	Y	Y

Table 15: External Pressure: Green Investor Pressure

The table shows the the estimation of the following panel fixed effect regression within each subclassification groups: $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Paris \times Greenownerpct_{j,t} + Greenholding_{j,t} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ 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 high short term leverage firms, $Greenholding_j$ is firm with high average level ownership percentage holding by green alliance. Holding data resourced from 13F fillings, with labeling green institution holders under Net Zero Alliance, Climate 100 and Global Fossil Fuel Divestment Database. $\delta_{j,t}$ 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. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Toxic Index Climate100	(2) Toxic Index GGFD	(3) Toxic Index NetZero
Paris×ST_Debt	-0.58099***	-0.56307***	-0.56307***
	(0.16977)	(0.18306)	(0.18306)
Green_holding	0.18803	0.18715	0.18715
	(0.30839)	(0.30533)	(0.30533)
Paris×$ST\_Debt \times Green\_holding$	-0.24628	-0.21499	-0.21499
	(0.24232)	(0.27892)	(0.27892)
Mean Dep.Var.	-1.637	-1.637	-1.637
Obs.	18975	18975	18975
R^2	0.524	0.523	0.523
Year FE	Y	Y	Y
Operator-supplier FE	Y	Y	Y
Geo FE	Y	Y	Y
Firm Control	Y	Y	Y
Well Control	Y	Y	Y

Table 16: Internal Governance: Green Innovation and Green Board

We use the following model to estimate firm's internal green governance, $Green_{j,t} = \alpha + \beta_1 \times Paris \times 1\{\text{ST\_Debt}_j\} + \gamma_j + \theta_t + \epsilon_{j,t}$ where $Green_{i,j,t}$ is firm j's green property at time t, Properties including logarithm of Green Patent labeled with CPC Y02 classification, Patent data resourced from PatentView; a Dummy variable indicating whether firm j have a green board in year t, logarithm of green board numbers count, green board data resource from Proxy Statement DEF14-A file. $Paris$ is an indicator of years after Paris agreement, $1\{\text{ST\_Debt}_j\}$ is a dummy of high short-term ratio firms, γ_j is firm fixed effect when needed, θ_t is the time fixed effect. $*, **, and***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Green Patent	(2) Green Committee	(3) Green members
Paris×ST_Debt	-0.08697	0.36678***	0.57545***
	(0.05780)	(0.11384)	(0.18492)
Mean Dep.Var.	0.423	0.363	0.557
Obs.	301	303	303
R^2	0.973	0.189	0.202
Year FE	Y	Y	Y
Operator FE	Y	N	N

Table 17: Green Board: Probit Regression and Marginal Effect

This table reports the Probit regression estimates and corresponding average marginal effect for the $Paris \times ST\_Debt$ variable. The dependent variable is a binary indicator for whether the firm has a green board resourced from Proxy Statement DEF-14A. Standard errors are reported in parentheses. Marginal effects are computed using the `margins` command. In columns (2) regression controls for logarithm of total asset, Tobin's Q, Capex Ratio, Profitability, Dividend Ratio, resourced from Compustat. $*, **, and *{**}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	No Controls		With Controls	
	Coef.	Marg. Eff.	Coef.	Marg. Eff.
Paris×ST_Debt	0.931***	0.314***	0.570***	0.165***
	(0.154)	(0.042)	(0.189)	(0.052)
Log Total Asset			0.211***	
			(0.073)	
Tobin's Q			0.220	
			(0.192)	
Capex/Total Asset			-2.387**	
			(1.112)	
Profit			0.007	
			(0.607)	
Dividend			5.888	
			(8.030)	
Observations	303		287	
Pseudo R^2	0.0950		0.2274	
Log Likelihood	-179.66		-147.61	

Table 18: Two-Stage Regression Results: Oil Supply IV Strategy

The first stage regresses monthly log oil price returns on exogenous oil supply shocks from Känzig (2021). $\Delta\log(\mathrm{WTI})_t = \gamma_0 + \gamma_1 \cdot \mathrm{OPEC}_t + u_t$. The fitted value is then used in the second-stage `ivreghdfe` regression. $Toxic\_Index_{i,j,s,g,t} = \beta_0 + \beta_1 \cdot \Delta\widehat{\log(\mathrm{WTI})}_t + \beta_2 \cdot \left(\Delta\widehat{\log(\mathrm{WTI})}_t \times 1\{\mathrm{ST\_Debt}_j\}\right) + \beta_3 \cdot \left(\Delta\widehat{\log(\mathrm{WTI})}_t \times 1\{\mathrm{ST\_Debt}_j\} \times Paris\right) + \beta_4 \cdot (Paris_t \times 1\{\mathrm{ST\_Debt}_j\}) + \theta_i + \varepsilon_{i,j,s,g,t}$. Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	1st Stage	**2nd Stage**	**2nd Stage**	**2nd Stage**
Panel A: First Stage	$\Delta\log(\mathrm{WTI})$			
OECD supply surprise	1.2437***			
	(0.375)			
Observations	240			
R-squared	0.044			
Panel B: Second Stage		Toxic_Index	Toxic_Index	Toxic_Index
$\Delta\widehat{\log(\mathrm{WTI})}$		0.011	0.021***	0.020***
		(0.009)	(0.008)	(0.006)
$\Delta\widehat{\log(\mathrm{WTI})} \times STDebt$		-0.016	-0.022**	-0.021***
		(0.012)	(0.010)	(0.008)
$\Delta\widehat{\log(\mathrm{WTI})} \times STDebt \times Paris$		0.017***	0.026***	0.017*
		(0.006)	(0.006)	(0.009)
$STDebt \times Paris$		-0.873**	-0.879***	-0.658***
		(0.346)	(0.288)	(0.233)
Weak-ID test (K-P F)		636.404	829.272	339.416
Clusters		Operator	Operator	Operator
Well Controls		Y	Y	Y
Firm Controls		N	Y	Y
Operator_supplier FE		N	N	Y
Year, State FE		N	N	Y
Observations		29421	28626	18975
R-squared (centered)		0.200	0.281	0.059

Table 19: Alternative Financing Access

We re-estimate the following empirical model to explore firm pollution heterogeneity excluding 3,6 and 8 large firms. $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ 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 depends more on short term debt financing. $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect for the controlling of firm's access of toxic chemicals. λ_g is state level fixed effect, ϕ_t is the year fixed effect. All regressions are controlled for well production properties such as logarithm of well vertical depth, logarithm of well horizontal length, logarithm of well water usage, well levels data are resourced from FracFocus. All regressions are also controls with firm level characteristics resourced from Compustat like logarithm of Total Asset, Tobin's Q, Capex to Total Asset, Profitability, Dividend Ratio, Tangibility, Operating Expense, Sale Percentage, and Oil Beta. Standard errors are clustered at operator level and are given in parentheses. $*, **, and ***$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
VARIABLES	toxic1	toxic1	toxic1
Drop	Top3	Top6	Top8
Paris$\times ST_Debt$	-0.382***	-0.330*	-0.451***
	(0.101)	(0.180)	(0.156)
Log True Vertical Depth	0.0801*	0.101**	0.101*
	(0.0434)	(0.0405)	(0.0502)
Log Horizontal Length	0.0565	0.102***	0.129***
	(0.0342)	(0.0304)	(0.0353)
Log Water Volume	-0.191***	-0.193***	-0.195***
	(0.0349)	(0.0262)	(0.0298)
Log(Total Asset)	-0.269	-0.223	-0.149
	(0.240)	(0.262)	(0.268)
Q	-0.458*	-0.566**	-0.467*
	(0.244)	(0.269)	(0.256)
Capex/Total Asset	0.284	0.346	0.0158
	(0.703)	(0.652)	(0.638)
Profit	0.0408	0.00543	0.170
	(0.419)	(0.423)	(0.444)
Dividend/Total Asset	-3.732	14.28	18.74
	(13.13)	(9.251)	(13.40)
Tangibility	1.347*	0.376	0.766
	(0.797)	(0.701)	(0.805)
Log(SGA/Sale)	-0.0468	-0.139	-0.122
	(0.0843)	(0.109)	(0.133)
Delta Sale	-0.0969	-0.191	-0.183
	(0.141)	(0.161)	(0.151)
Oil Beta	2.866	14.95	6.561
	(21.50)	(20.74)	(19.54)
Observations	15,717	11,596	9,246
R-squared	0.519	0.561	0.535
Year FE	Y	Y	Y
Operator-supplier FE	Y	Y	Y
Geo FE	Y	Y	Y

Table 20: Bank Lending Access

We re-estimate the following empirical model to explore firm pollution heterogeneity when receiving new loans. $Toxic\_Index_{i,j,s,g,t} = \alpha + \beta_1 \times 1\{\text{ST\_Debt}_j\} \times Prais \times Bank\_Loan_{j,t} + \delta_{j,t} + \theta_i + \gamma_{j,s} + \lambda_g + \phi_t + \epsilon_{i,j,s,g,t}$ 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 depends more on short term debt financing. $Bank\_Loan_{j,t}$ is a dummy to indicate whether firm j has received bank loans. $\delta_{j,t}$ is firm level controls at year t, θ_i is well level controls, $\gamma_{j,s}$ is operator-supplier fixed effect for the controlling of firm's access of toxic chemicals. λ_g is state level fixed effect, ϕ_t is the year fixed effect. All regressions are controlled for well production properties such as logarithm of well vertical depth, logarithm of well horizontal length, logarithm of well water usage, well levels data are resourced from FracFocus. All regressions are also controls with firm level characteristics resourced from Compustat like logarithm of Total Asset, Tobin's Q, Capex to Total Asset, Profitability, Dividend Ratio, Tangibility, Operating Expense, Sale Percentage, and Oil Beta. Standard errors are clustered at operator level and are given in parentheses. $*, **, and *{**}$ indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) Toxic Index All Bank	(2) Toxic Index Green Bank
$Paris \times ST\_Debt$	-1.21575***	-1.00159***
	(0.25288)	(0.27186)
$Bank\_Loan$	-0.23905	-0.27217*
	(0.15512)	(0.15311)
$Paris \times ST\_Debt \times Bank\_Loan$	0.78482***	0.56848**
	(0.20935)	(0.22951)
Mean Dep.Var.	-1.636	-1.636
Obs.	18961	18961
R^2	0.533	0.531
Year FE	Y	Y
Operator-supplier FE	Y	Y
Geo FE	Y	Y
Well Controls	Y	Y
Firm Controls	Y	Y

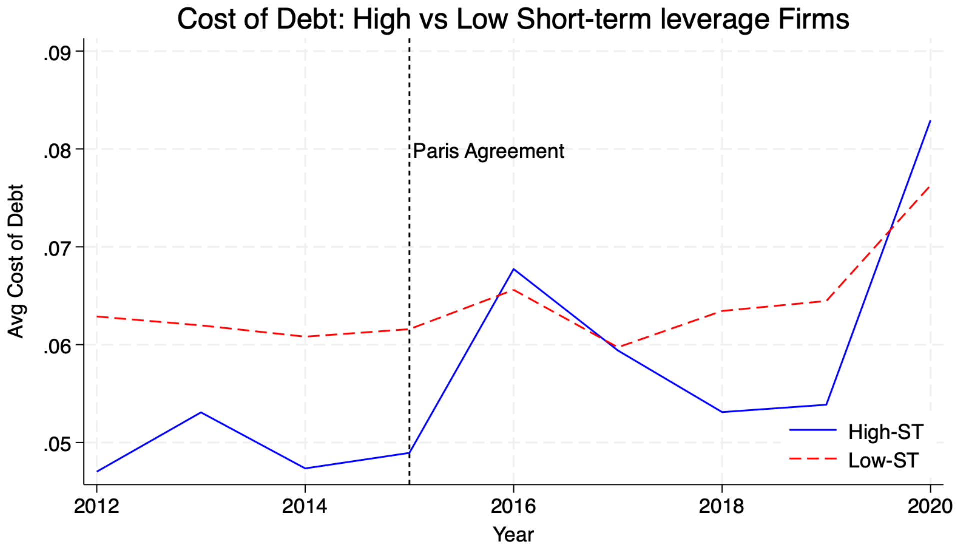


Figure 1: Average Cost of Debt

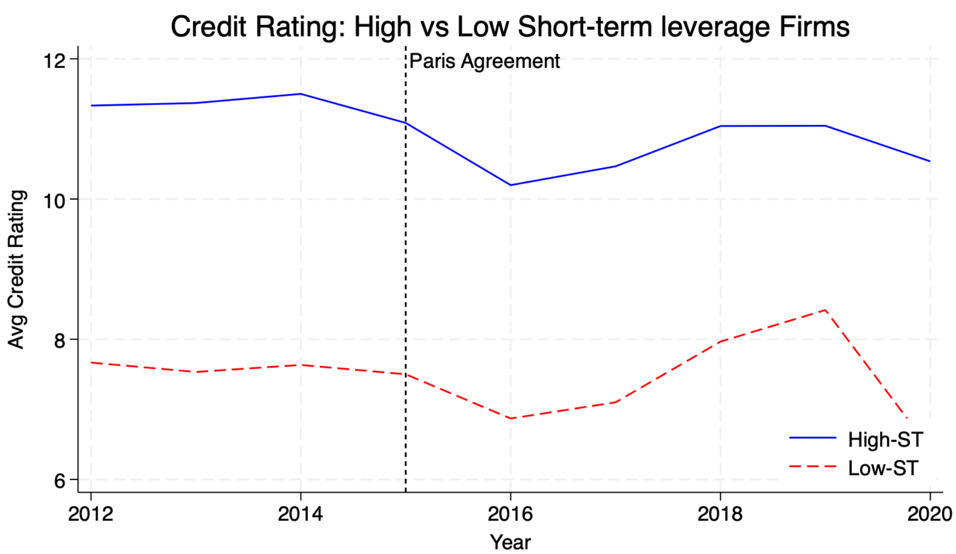


Figure 2: Average Credit Rating

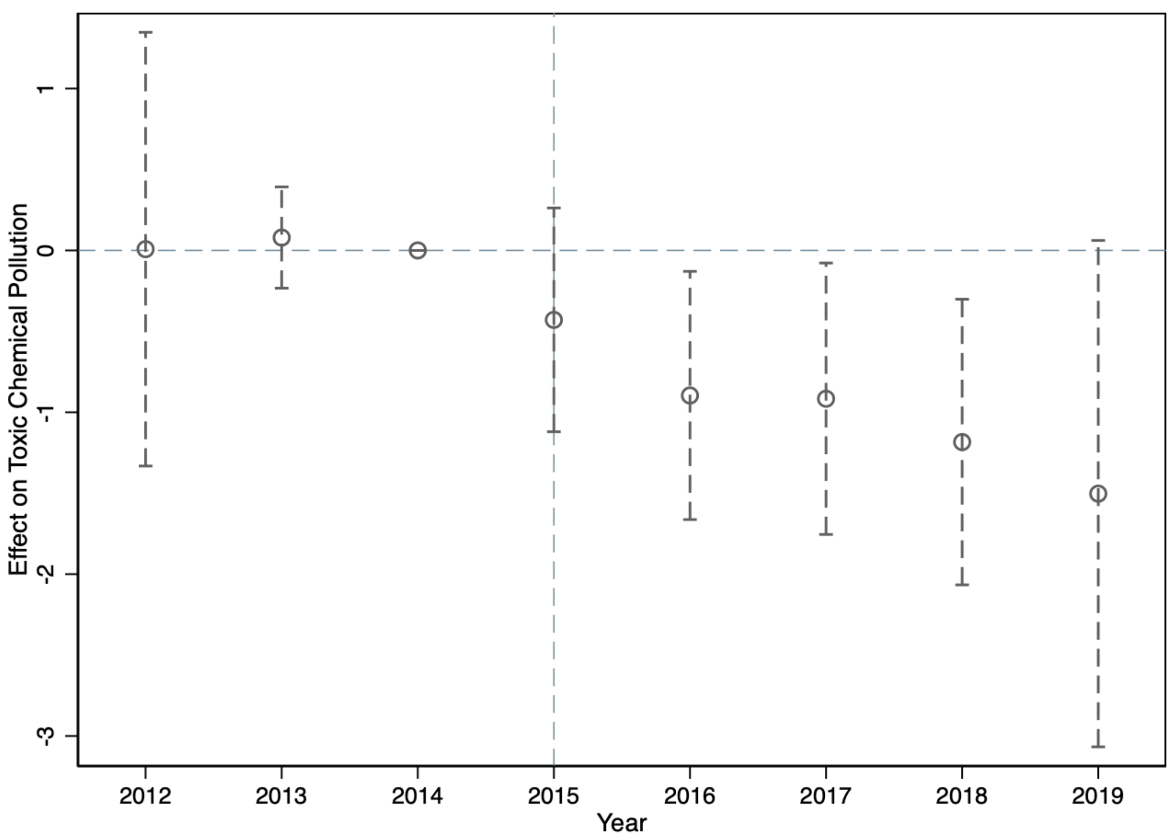


Figure 3: Parallel Trend for Policy Shock

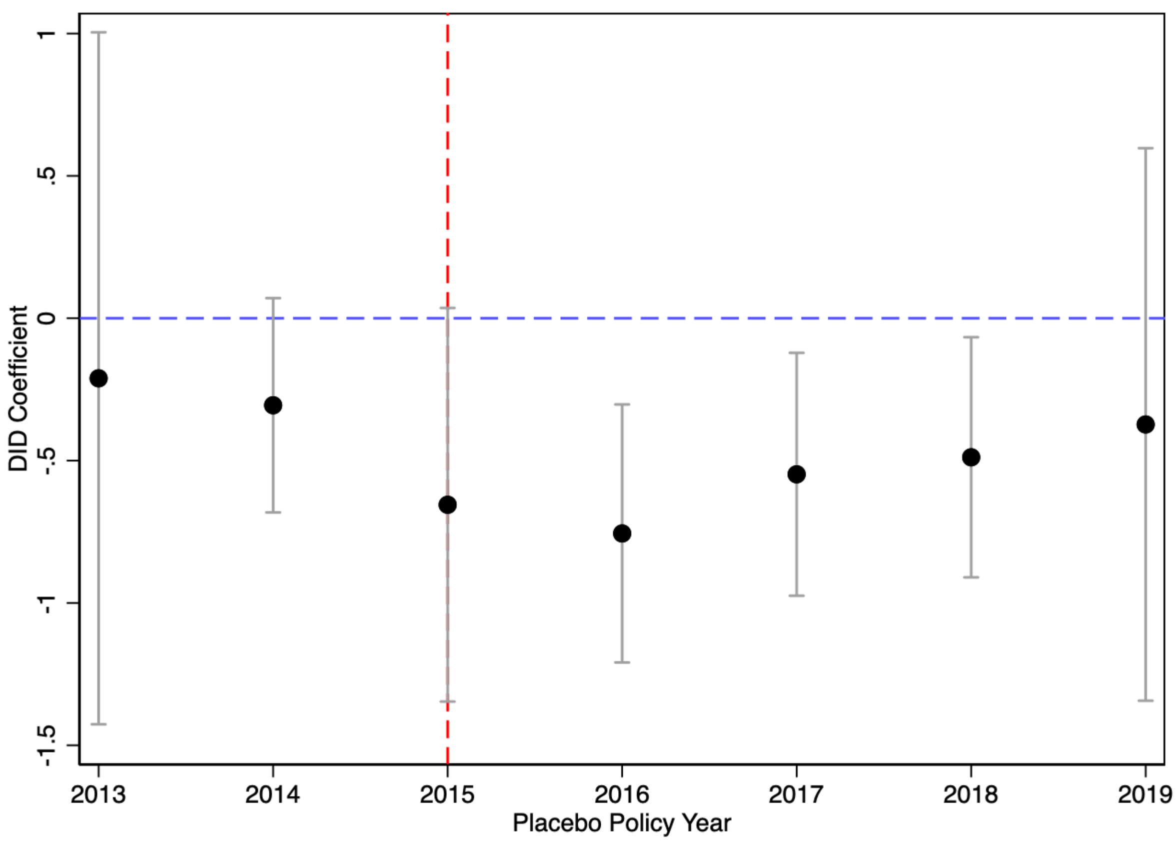


Figure 4: Placebo test for Policy Shock

Appendix

Appendix A1: Purpose of Toxic and Chemical Usage

Fracturing fluids are injected into wells to generate conductive fractures and circumvent formation damage near the wellbore in hydrocarbon-bearing zones. This procedure substantially increases the productive surface area of the reservoir compared with its condition before fracking. A variety of chemical additives are used to ensure that the fluid possesses specific characteristics such as viscosity, friction reduction, compatibility with the formation, and control over fluid loss.

The hydraulic fracturing process employs two primary types of materials: fracturing fluids and proppants. The fluids traditionally used in shale well fracturing treatments consist of either water-based solutions or mixed slickwater fluids. The latter refers to water-based fluids blended with friction-reducing additives such as potassium chloride. Determining the appropriate fracturing fluids, additives, and proppants is a subjective process that takes into account factors such as formation evaluation, laboratory test results, and field experience. The most fundamental and widely used technique for stimulating unconventional gas wells is slickwater fracturing.

Chemical additives used in hydraulic fracturing serve several purposes and are categorized into subgroups including fluid-loss additives, clay stabilizers, gel breakers, bactericides or biocides, and pH control agents. Acidizing treatments aim to enhance the productivity or injectivity of a well.

Proppants—typically composed of sand or synthetic, sand-like materials such as silica sand, resin-coated silica sand, or ceramic beads—are used to maintain fracture openness, thereby facilitating the movement and extraction of crude oil and natural gas. The effectiveness of a proppant is evaluated by its ability to preserve fracture conductivity, and the optimal selection is achieved by ensuring sufficient fracture continuity. Over time, production rates tend to decline more rapidly with larger proppant sizes, as they are constrained by the permeability of the formation matrix. Beyond fracture conductivity, other important considerations in multistage fracturing include flow convergence in transverse fractures, proppant transport in low-viscosity fluids, and proppant compression under lowconcentration conditions.

To categorize and determine the specific uses of toxic chemicals in the fracturing process, we consulted relevant chapters from the *Handbook of Hydraulic Fracturing* (Speight, 2016). We first cataloged the chemical types and their intended purposes as outlined in the handbook, and then employed fuzzy matching against the reported purposes in the FracFocus dataset. We retained the results of this matching for subsequent analysis. The keywords used for the matching procedure are listed in the appendix. Our objective is to identify which functional purposes most frequently involve toxic chemicals and which have reduced their use of such substances over the past decade.

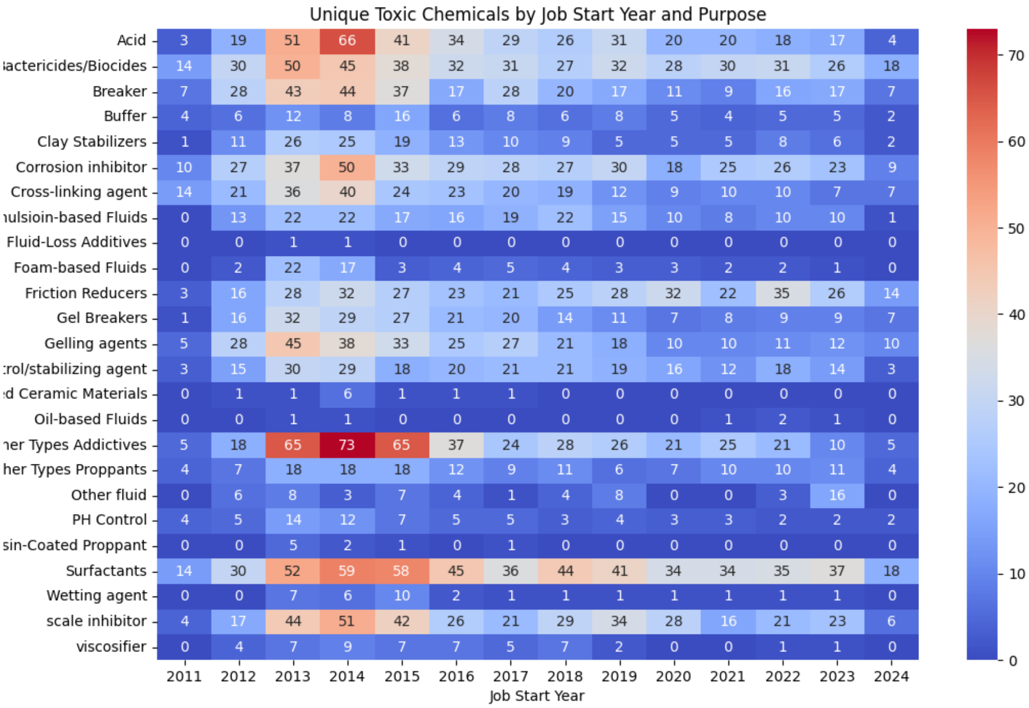
Figure **??** provides a detailed visualization of toxic chemical applications—identified by the hazard designation "Danger"—across various fracturing operations since 2011. Each cell within the heatmap is color-coded to represent the count of distinct toxic chemicals employed, with the gradient transitioning from blue (lower count) to red (higher count). The analysis of the heatmap yields several notable observations:

(i) There was a distinct peak in the number of unique toxic chemicals used during the period from 2013 to 2015.

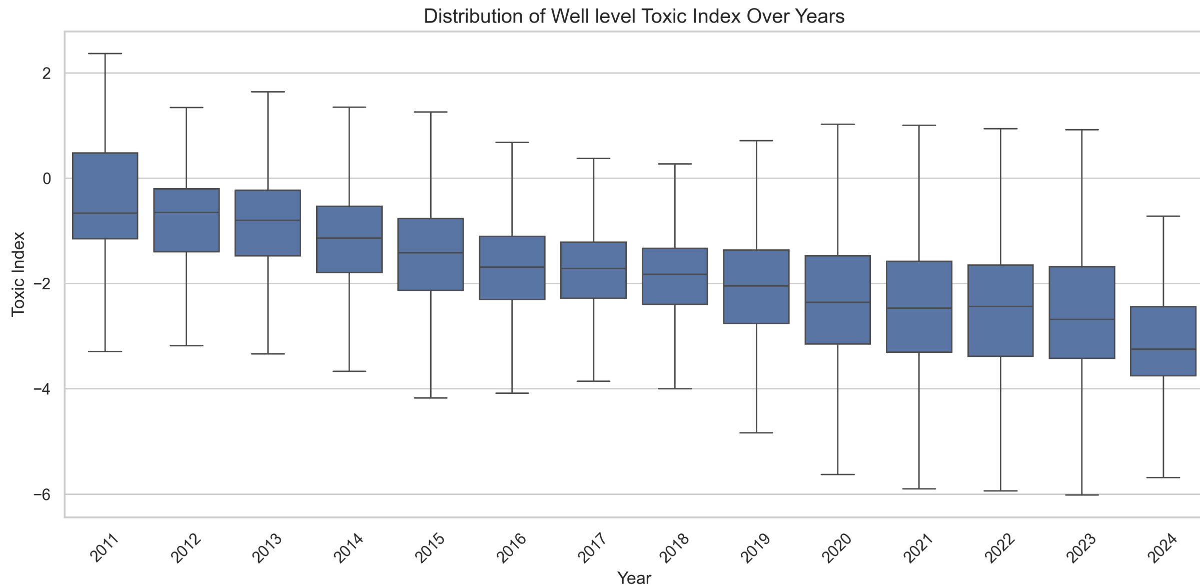
(ii) The subsequent reduction in chemical diversity is likely attributable to the introduction of stricter regulatory frameworks and enhanced disclosure transparency.

(iii) Substantial variability exists across different operational purposes; functions such as acid treatment, bactericides/biocides, corrosion inhibitors, general additives, surfactants, and scale inhibitors consistently exhibit higher chemical diversity.

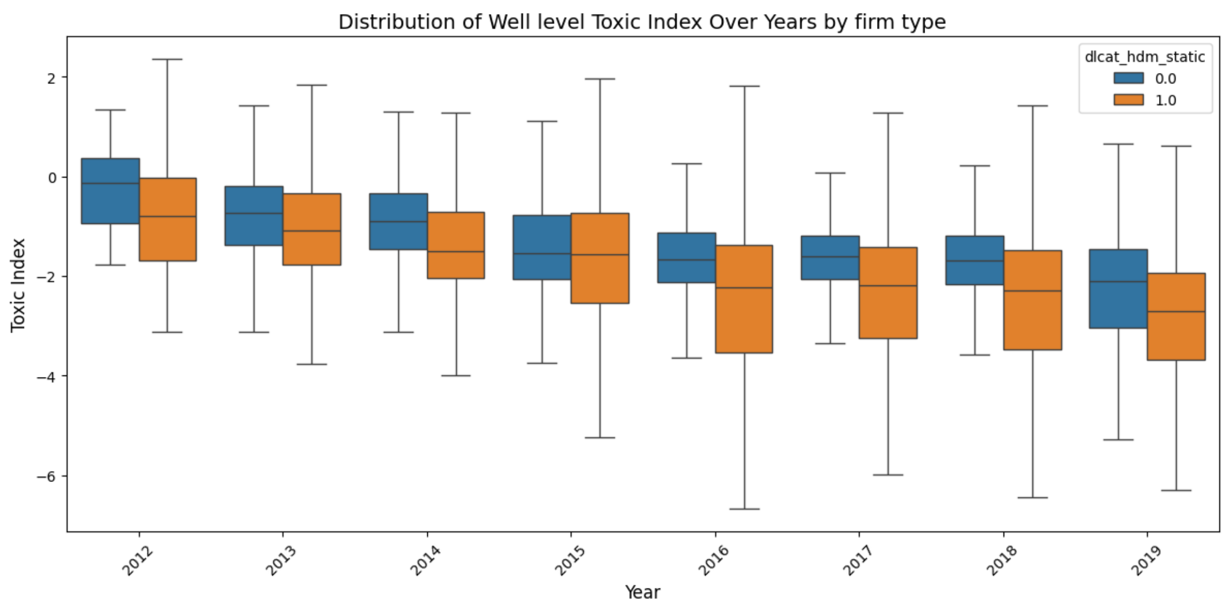
(iv) The observed decline in the use of toxic chemicals within each category suggests an ongoing industry-wide shift toward minimizing the use of hazardous substances in specific applications.



A1: Toxic chemicals usage type per year classified by purpose



A2: Toxic Index Distribution



A3: Toxic index yearly distribution within high short-term leverage firm

Type	Purpose	matched
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 A4: 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 A5: Purpose Matching Word

Appendix A2: Key Regulatory Developments Related to Hydraulic Fracturing

1. **Safe Drinking Water Act (SDWA) and the "Halliburton Loophole."** The Safe Drinking Water Act (SDWA) is the primary federal law ensuring the quality of Americans' drinking water. However, the 2005 Energy Policy Act created an exemption—commonly known as the "Halliburton Loophole"—that excluded hydraulic fracturing activities from SDWA regulation. Between 2014 and 2015, growing public pressure and environmental advocacy efforts sought to close this loophole, arguing that fracking should be subject to the same federal groundwater protection standards as other industrial activities.

2. **Bureau of Land Management (BLM) Hydraulic Fracturing Rule (2015–2017).** In March 2015, the U.S. Bureau of Land Management (BLM) issued a rule aimed at strengthening environmental safeguards for hydraulic fracturing on federal and tribal lands. The rule required operators to disclose the chemical composition of fracturing fluids and to implement stronger well integrity and wastewater management standards. However, the rule faced legal challenges and was ultimately rescinded in early 2017.

3. **Toxic Substances Control Act (TSCA).** The TSCA regulates the manufacture, processing, and distribution of toxic or hazardous substances. Under this act, companies are required to report the discharge of pollutants once they reach specified thresholds. This ensures that the public and regulatory agencies are informed and can monitor the environmental impact of shale gas development.

4. **State-Level Water Withdrawal Regulations.** Individual U.S. states have introduced strict limits on water withdrawal for shale gas development to prevent water waste and pollution. For example, Louisiana restricts the scope of water withdrawal; New York requires that withdrawals be evaluated and licensed by local regulatory agencies; and Michigan has established a water withdrawal assessment system to ensure that industrial usage does not impair public or ecological needs.

Table A1: Major U.S. Regulations Affecting Hydraulic Fracturing (2015–2016)

Regulation	Proposal Time	Implementat Time	Termination / Expiration	Main Provisions	Impact on Hydraulic Fracturing Industry
BLM Hydraulic Fracturing Rule	2013 draft, finalized 2015	Published Mar. 2015, effective Jun. 2015	Repealed in 2017	Well integrity tests, wastewater container storage, chemical disclosure	Higher costs, disclosure pressure, scope limited to federal/tribal lands
EPA Methane & VOC Standards (CAA)	Proposed Aug. 2015	Effective May 2016	Weakened 2017–2020, strengthened again in 2021	Limits on methane/VOCs, mandatory green completions, LDAR requirements	Increased equipment investment and operating costs, disproportionate burden on small independents
TSCA Reform (Lautenberg Act)	Proposed Mar. 2015	Signed Jun. 22, 2016	Permanent	Mandatory risk assessments, expanded EPA authority, strengthened information disclosure	Toxic chemicals subject to review, need for substitutes, rising compliance/disclosure costs