Does Private Equity Ownership Make Firms Cleaner? The Role Of Environmental Liability Risks*

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Abstract

Private equity (PE) ownership leads to a 70% reduction in the use of toxic chemicals and a 50% reduction in CO2 emissions. The reduction is identified by comparing projects from PE-backed firms to their close geographical neighbors using novel satellite imaging and administrative datasets from the oil and gas industry. Exploiting a novel natural experiment, I find that PE ownership's impact on pollution is negatively related to plausibly exogenous increases in regulatory risks, contrary to what either a non-pecuniary or technological upgrade channel would predict. Using specific PE deals from the energy industry, I find that PE control rather than the financing they provide is the main driver behind the results. Additional tests support the view that PE firms better monitor the management team and reduce the pollution of their portfolio companies to maximize both (1) long-term cash flows and (2) the exit value as cleaner assets trade at a higher price.

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According to Preqin, 40% of private equity (PE) acquisitions during the last decade in the US are in industries that generate a significant quantity of pollution, such as the energy, infrastructure and heavy industy sectors. Pollution is an important contributor to societal well-being as it affects public health, worker productivity, house prices and environmental sustainability. As such, it is highly regulated and subject to the "most significant federal interventions into markets in the postwar period" (Greenstone (2002); Currie and Walker (2019)). Environmental regulation is likely to increase, as $376 billion investment per year are required to reduce greenhouse gas emissions to the level fixed during the Paris Agreement of December 2015. Part of these investments will likely be financed by PE firms given their current industrial exposure and the size of the asset class, that reached 4.1 trillion in assets under management in 2019.

It is theoretically unclear whether PE owned firms have different incentives than privately-held or publicly traded firms in overcomplying to pollution limits. General partners of PE funds have high-powered incentives to increase the profits of the companies they acquire. On one hand, General partners of PE funds could create shareholder value at the expense of other stakeholders, as observed in other regulated industries, such as the education and health care sectors (Eaton, Howell, and Yannelis (2019); Gupta et al. (2020)). On the other hand, private equity ownership leads to better corporate governance (Gompers, Kaplan, and Mukharlyamov (2016)), reduces financial constraints (Boucly, Sraer, and Thesmar (2011)) and transfers industry knowledge (Bernstein and Sheen (2016)), which could lead to lower pollution.

The question is empirical, but measuring how PE ownership affects pollution is difficult. The first challenge is to find data on pollution, especially for small and private firms. The second challenge is an identification problem, as PE ownership is correlated with omitted forces —such as changes in production— that if not perfectly observed, make causal inference difficult. To address each of these challenges, I focus the empirical analysis on the US oil and gas industry, that attracts an important fraction of PE capital[1] and produces a significant amount of pollution[2].

To handle the first challenge, the lack of detailed information on pollution, I merge project-level administrative data on the chemicals used in the production process for 139,809 US wells fracked between 2010 and 2019 with detailed information on the features of each well from commercial datasets. I also build on advances in satellite remote sensing (Elvidge et al. (2013)) to create and validate a database on whether

[1]According to Preqin and during the last decade, the total amount in value of PE add-on, buyout, growth capital in the United States is higher in the oil and gas industry than in the health care, retail, education and insurance sectors (See Figure 1 for details).

[2]According to the 2010 decennial Census, more than 55 million households live in a shale basin and potentially expose to toxic chemicals. Flaring is an important contributor of CO2 emission. Given the importance of such pollution, the World Bank has launched the Zero Routine Flaring initiative, aiming at suppressing routine flaring by 2030 (Bank (2015)). In 2018, 28% of methane emissions come from the oil and gas industry in the US (source: EPA), although there is evidence that this reported pollution is far below the actual ones (Shindell et al. (2009)). Methane is one of the most potent greenhouse gases and traps 84 times more heat per mass unit than CO2 in the first 20 years.

firms practice flaring at the well level, which consists in burning the gas contained in oil wells to save the fixed cost of connecting the well to a pipeline or to treat the gas (Elvidge et al. (2009)). These two variables —whether firms are releasing toxic chemicals and if they are flaring— give a novel picture of environmental corporate policies.

To handle the second challenge and mitigate the influences of omitted variables, I exploit the institutional features of the oil and gas industry. Nearby projects drill in the same rock formation, have the same distance to pipelines and local suppliers of chemicals, and the same exposure to local population and housing. All these variables drive the marginal cost and benefit of polluting. Therefore, I compare each project from firms that receive PE investments to projects that are completed during the same year and in the same area as non-PE backed firms.

My analysis shows that PE ownership leads to a 70% reduction in the use of toxic chemicals and 50% in flaring. I take several steps to ensure that this reduction is not fully driven by an omitted variable. Before the acquisition and after controlling for geographically close projects, there are no pre-trends and rarely any differences in project-level characteristics between acquired firms and the others. Next, I drop core activities of a firm that are most likely to drive the acquisition decision of the PE and focus the analysis on marginal projects. For instance, if a firm has 95% of its activity in the Bakken and 5% in the Barnett formation, then I drop projects from the Bakken and look at the impact of PE ownership on pollution for projects from the Barnett formation. The reduction remains stable. Although the identification approach does not rely on a natural experiment, the results found put several hurdles on a non-causal interpretation of the reduction.

I then dedicate the second part of the paper to understanding the economic forces that drive this reduction. PE ownership could alleviate a financial constraint hindering the investment in pollution abatement projects. PE sponsors are deep pocket investors, that typically have existing funds with undrawn capital (Gompers, Kaplan, and Mukharlyamov (2016)) and are more likely to inject capital to their firms in case of financial distress (Hotchkiss, Strömberg, and Smith (2014)). An ideal test for the financial constraint channel would be to observe a reduction in pollution when a PE firm provides financing to a company without having the ability to control the management team.

To approximate this kind of test, I rely on a type of PE deal that exists only in the oil and gas industry: DrillCo contracts. This paper is the first, to my knowledge, to exploit and document this class of PE contracts. In such contract, the PE firm provides capital to several well tranches against part of the working interest in these projects. Interestingly for my empirical design, projects are funded without a change in the level of debt and the PE firm does not control the firm's management. I show that firms do not reduce pollution when the PE sponsor has no ability to control their portfolio companies when comparing projects between firms with DrillCo contracts with their closest neighbors.

Next, I provide evidence supporting the view that the reduction in pollution is consistent with shareholder value maximization. A PE sponsor provides a form of ownership that better aligns the incentives of owners with the corporate managers (Morris and Phalippou (2020), Gompers, Kaplan, and Mukharlyamov (2016)). The use of greater debt disciplines managers, and PE firms increase managerial incentives to maximize profit through performance-based pay. General partners, on behalf of limited partners, control the board of their portfolio companies and actively monitor them. Therefore, PE ownership leads to lower pollution when it maximizes shareholder value, as I show using three specific tests.

First, agency frictions create an incentive for managers to artificially boost short-term earnings at the expense of long-term shareholder value, as short-term earnings are used as a signal for future performance by external financial investors (Stein (1989), Grenadier and Malenko (2011)). One way to boost short-term earnings could be through more pollution. Consistent with this view, I show that suppressing flaring has a high payback period, that is, not connecting the well to a pipeline saves several million dollars when the project begins.[3] However, the loss in earnings is diffuse in time and difficult to detect for shareholders with limited information. According to new data that I collect from the Oil & Gas division of the North Dakota Department of Mineral Resources, on average, half of the production of gas that is flared is produced between the second and fifteenth year of the well. PE firms monitoring of the company reduces the agency frictions between managers and shareholders, leading to the creation of long-term shareholder value.

Second, I show that the reduction in pollution caused by PE ownership is lower following plausibly exogenous negative shocks in the future expected cost of using pollutants, consistent with an incentive to maximize expected profit. Specifically, I show that PE-backed firms reduce pollution *less* when the probability of having a new regulation is lower, using a natural experiment that is novel to both the finance and economic literature. Between 2015 and 2018, a preliminary injunction from a Federal Court, a subsequent Court judgment and a decision in 2017 from the Trump administration blocked the ability of the Bureau of Land Management (BLM) to regulate fracking in Native American reservations and federal lands. I exploit these shocks in a double difference–in-differences strategy. Roughly speaking, I compare the impact of lower regulatory shock on pollution for projects located in areas regulated by the BLM, with their closest projects from non-affected areas for each firm. Then, I compare this relative difference for PE-backed firms

[3] Most of the cost of reducing flaring is paid at the beginning of the project. First, On-site facilities and equipment, such as dehydrators and compressors needs to be installed close to the well. According to the Interstate Natural Gas Association of America (INGAA) they were on average \$210,000 per well in the Bakken. Then, the well needs to be connected to a pipeline and the price is a function how far the well is to a pipeline and the diameter of the connecting facility. According to the INGAA, the prices in 2017 range from \$29,000 to \$167,000 per mile for a diameter range between 2 and 22 inches.

and the others and show that this difference increases when regulatory risks are lower. The interpretation of this increase is that PE-backed firms reduce pollution less for projects located in areas with lower regulatory risk –namely, Native American reservations and federal lands– compared to the projects in their surrounding but located in areas with higher regulatory risks. This is consistent with the view that PE-backed firms decision on the usage of pollution is the result of a cost and benefit analysis, where regulatory risk is taken into account.

The fact that the reduction in pollution is a function of changes in regulatory risks is compelling evidence against the view that this reduction is a byproduct of technological upgrades that follow the acquisition. If the effect is fully driven by general partners transferring technological knowledge to their portfolio companies, thus allowing them to produce in a cleaner way, then we should observe a reduction in pollution that is independent from changes in regulatory risks in Native Americans and federal lands. The exogeneity assumption of the regulation shock to unobserved technological changes is credible, given the spatial and timing variations of the shock. The boundaries of Native American reservations and federal lands were decided at the end of the nineteenth and beginning of the twentieth centuries and overlap shale basins in a quasi-random ways, as horizontal drilling and hydraulic fracturing were not discovered until the beginning of the twenty-first century. This quasi-random overlapping of shale boundaries and BLM areas is supported by both the absence of any pre-trend before 2015 and the balance in characteristics for projects around the borders of areas regulated by the BLM.

Third, I provide additional evidence of the role of agency frictions in the decision to pollute by looking at publicly listed companies. Bertrand and Mullainathan (2001) and Davis and Hausman (2020) suggest that shareholders from public listed companies in the oil and gas industries do not perfectly monitor their corporate executives and are thus able to extract a rent by being paid for outcomes not tied to their efforts. Consistent with the view that agency frictions matter for the decision to pollute, I find an increase in pollution after seven IPOs that took place between 2011 and 2019, using close neighbors' projects as a counterfactual. As an additional test that widely-held public firms lead to less monitoring of corporate managers and an incentive not to always invest in projects with a high payback period, I compare the decision to pollute for public firms around earnings forecasts. Firms that are close to missing the mean earning forecasts of their analysts are more likely to pollute, but I find no effect for firms that have their earnings above the mean earnings forecast of their analysts. This is consistent with the view that corporate executives abandon long-run investments to maximize their short-term profits in order not to miss their earning forecasts.

Reducing pollution also maximizes the PE value through a higher selling price of the portfolio company. PE firms have an investment horizon of five to ten years on average, which implies that they care more about the exit price than shareholders with a longer holding time. Selling a polluted asset is difficult because they expose the new owner to more environmental liability risks. Environmental liability encompasses any environmental cost associated with the asset, such as current and future compliance costs, cleanup costs implied by the releases of hazardous substances and any potential fines and litigation fees caused by environmental torts or trespass. It is difficult to know precisely the amount of environmental liability an asset contains and gathering information is costly. Potential buyers have different beliefs and information regarding the distribution of these risks. This creates a discount for assets that are polluted. If the selling price of an asset is lower than the risk-adjusted discounted value of its cash flow when the asset contains pollution, then it becomes optimal for an owner aiming to sell such an asset to make it cleaner. This behavior is consistent with economic models of product differentiation (Osborne and Pitchik (1987)), where there is a benefit to changing the amount of characteristic (pollution) to either increase the demand for a good (the portfolio company) or attract buyers with a higher valuation for that characteristic, who are thus willing to pay a higher price.

The fact that polluted assets are traded at a discount is confirmed using a new dataset of 987 oil and gas project transactions. Although the relationship is not identified using quasi-experimental variations, the relationship survives after the inclusion of a very detailed set of controls at the project-level that cannot be observed in other empirical settings, such as project characteristics, including observed potential of the project, and a location / basin fixed effect. I still find a negative relationship when I add a buyer and seller fixed effect, but the coefficient is imprecise as only 193 projects are exchanged more than one time by the same buyer and seller. Overall, this is consistent with the notion that polluted assets are traded at a lower price to compensate the future owner for higher expected clean-up costs.

One implication of the paper is that initiatives to decarbonize portfolios could come at the cost of increasing pollution in dirty industries by reducing the participation of investors that improve the corporate governance. Disinvestment from the fossil fuel sectors raises the cost of capital of firms in these industries, thus leading to lower production (Broccardo, Hart, and Zingales (2020), Heinkel, Kraus, and Zechner (2001)). This reasoning has driven an important set of private initiatives, such as the Portfolio Decarbonization Coalition (PDC), to disinvest from carbon intensive sectors. Financial investors and especially private equity firms do more than just provide financing, but also affect the corporate governance. PE ownership leads to a drop in managerial rents, thus lowering pollution in industries when it is profit-maximizing to do so.

Related literature This paper contributes to the literature on how PE ownership affects their portfolio companies. Previous papers have identified three theoretical channels explaining PE-induced operational changes: (1) a reduction in financial constraints (Boucly, Sraer, and Thesmar (2011)) (2) better corporate governance leading to more shareholder value creation (Eaton, Howell, and Yannelis (2019), Cohn, Nestoriak, and Wardlaw (2019), Lerner, Sorensen, and Strömberg (2011)), and (3) a transfer of knowledge from the PE to the firm (Bernstein and Sheen (2016), González-Uribe (2019)). Consistent with previous papers, I find important operational changes explained by better corporate governance following the PE acquisition, as the reduction of pollution maximizes long-term shareholder value. I also document a novel channel, that relates to the investment horizon of PE firms that need to exit within ten years and have an incentive to increase the selling price of their target company, thus leading to specific operational changes.

This paper also contributes to this literature by studying the impact of PE ownership on the persons incurring the cost of pollution, whereas most previous papers focus exclusively on consumers, workers and governments with the exception of Shive and Forster (2019). They study the impact of listing status on environmental externalities, albeit in an empirical setting that is different from this paper. They show that PE ownership is associated with an increase or no effect on pollution, while this paper documents a decrease.

This paper joins the literature examining environmental, social and corporate (ESG) performances, where the role of PE sponsors adds to the influences from supply chains (Schiller (2018)), CEO preferences (Di Giuli and Kostovetsky (2014)), financial constraints (Bartram, Hou, and Kim (2019), Kim and Xu (2017), De Haas and Popov (2019), Levine et al. (2019), Cohn and Deryugina (2018)), limited liability (Ohlrogge (2020), Akey and Appel (2020), Boomhower (2019)), and activist shareholders (Akey and Appel (2019), Naaraayanan, Sachdeva, and Sharma (2019)).

The remainder of the paper is organized as follows. Section 1 describes the institutional background of our empirical setting. It also outlines the main databases used in the paper. These components are crucial to understanding the identifying assumption. Section 2 provides the main result that PE ownership causes a reduction of pollution. Section 3 tests whether we observe such a reduction when the PE firm is just providing financing through a DrillCo contract. Section 4 provides several pieces of evidence consistent with a reduction driven by better monitoring of corporate executives. Section 5 shows that the reduction in pollution is consistent with an incentive to maximize the selling price of the portfolio company. Section 6 performs several sensitivity analyses to test the robustness of the results. Finally, section 7 concludes.

1 Institutional Background and Data

The U.S. onshore oil and gas industry provides several institutional features and datasets to study the role of PE ownership in the production of pollution. In this section I discuss in greater detail each of the components of my empirical setting.

1.1 Shale oil and gas drilling and pollution

The production of natural gas in the United States increased by more than 25% from 2007 to 2013 and the production of oil nearly doubled between 2009 (5.4 Mb/d million barrels of oil per day) and 2014 (9.4 Mb/d at year end 2014), following the discovery of hydraulic fracturing and horizontal drilling[4]. Horizontal drilling allows the exploitation of reserves that are located in a horizontal reservoir and that couldn't be exploited with a traditional vertical well. Hydraulic fracturing is the practice of creating cracks in the rock so that gas and oil can circulate to the well and be extracted. These cracks are made by injecting high-pressure water mixed with different chemical components. These technologies enable the exploitation of large, untapped reserves of hydrocarbons captured in porous and low-permeability rocks.

There are multiples ways through which the extraction of oil and gas, especially through hydraulic fracturing, generates pollution. The fracturing process is mixed with chemicals that can be highly toxic for humans. These components can come into contact with humans, either by the contamination of groundwater or leaks from storage tanks. Another way through which oil and gas activities generate pollution is by the practice of flaring. Flaring consists of burning the gas contained in oil wells instead of recovering it. The gas that is burnt allows the firm not to invest in infrastructure –such as connecting the well to a pipeline– that would allow its exploitation. The gas burnt can disperse toxic chemicals to the neighborhood thus contaminating the air.

This pollution is quantitatively significant. Toxic pollutants that are likely to contaminate groundwater exposed directly 18 million households that live at least one mile from a well (Konkel (2017)). This number will grow as the US onshore production expands. Flaring is also an important contributor of global warming, although estimates are hard to find. Worldwide flaring burnt 145 billion cubic meters in 2018, which is equivalent to the total annual gas consumption of Central and South America. Given the importance of such pollution, the World Bank has launched the Zero Routine Flaring initiative, aimed at suppressing routine flaring by 2030 (Bank (2015)). Each day, flaring in the shale oil fields of North Dakota and South Texas burns 1.15 billion cubic feet of natural gas, which is equivalent to provide power for 4 millions homes or

[4] Oil production from fracked wells accounts for nearly half of US production EIA (2017)

driving nearly 5 million cars for a day. Yemen, Algeria and Iraq could meet their national reduction targets under the UN Paris Agreement just by eliminating flaring (Elvidge et al. (2018)).

The fracking industry is an interesting setting to define over-compliance, as hydraulic fracturing is exempt from several federal environmental laws. The release of toxic components in natural surface waters –such as lakes, rivers, streams, wetlands and coastal areas– is controlled in the United States by the Clean Water Act (CWA) and Safe Drinking Water Act (SDWA). The practice of hydraulic fracturing has been exempt from the SDWA since the Energy Policy Act of 2005[5]. This exemption has been highly controversial[6]. The oil and gas industry is also exempt from important permitting and pollution control requirements that are included in the CWA. I exploit these exemptions in my empirical analysis to define a variable of overcompliance. I select chemicals that are reported as toxic and hazardous for human health as reported in the United States House of Representatives Committee on Energy and Commerce of April 2011. Health scientists agree on the high degree of toxicity of these chemicals and anecdotal stories of local contamination with these components have been reported. As a result, these chemicals have a high mediatic exposure and have been reported by several environmental organizations as causing a threat to human health. Except for one, they are all regulated by the SDWA and CAA but subject to the exemption in the fracking industry. Table 1 reports the name of all the chemicals used in the analysis, as well as their CASN number and whether or not they are regulated by SDWA and CAA.

1.2 Oil and gas datasets and its regulations

The Ground Water Protection Council and the Interstate Oil and Gas Compact Commission launched FracFocus in April 2011, a repository of chemicals used during the fracking process. This was first a voluntary disclosure database to report the chemicals used for each well, but states slowly began to impose mandatory reporting to this database. Figure A.1 reports the year from which the reporting started to become mandatory by states. By 2013, 75% out of 28 oil and gas-producing states had a reporting to FracFocus that was mandatory. In 2015, the latest states (Kentucky and North Carolina) had a mandatory reporting to FracFocus.

[5]This exemption does not apply for diesel fuels hydraulic fracturing

[6]In 1997, the Environmental Protection Agency (EPA) was ordered by a decision from the the U.S. Court of Appeals of the 11th Circuit to include hydraulic fracturing in SDWA. In 2001 a special task force lead by Vice President Dick Cheney asked that Congress exempt hydraulic fracturing from the SDWA. At the same time, the EPA released a controversial report in 2004 claiming that hydraulic fracturing "poses little or no threat" to drinking water. As a result, the 2005 energy bill witdrawn the ability of EPA to regulate hydraulic fracturing activities. This exemption was highly controversial. In March of 2005, evidence of potential mishandling in the EPA study of 2004 was officially found. Moreover, the Oil and Gas Accountability Project (OGAP) organized a review of the 2004 report and found proof that EPA removed from the initial drafts parts that suggested that unregulated fracturing can be detrimental to human health.

This administrative dataset allows us to investigate the input used during the production process with an extremely fine degree of granularity. The data report information at the well level, such as its longitude and latitude, its API14 number (the regulatory ID of the well), the date at which the well job started and was completed, and the name of the operator. It also contains the total number of chemicals used with their CAS number. The CAS number allows us to perfectly identify the presence of a toxic chemical. Operators can report a chemical as confidential, and in this case, the CAS number will be hidden.

I merge the API14 number with detailed data from the private vendor Enverus, which provide information on the production (for the first six months of oil and gas extracted), the horizontal length, the vertical depth, and the basin on which the well is drilled. These variables are important, because the first six months of production predicts with great accuracy the overall future well production. Once the well starts producing, it follows a stable and predictable decline curve[7]. The horizontal and vertical size of the well captures the type of technology used (whether it is an horizontal well) and the cost required during the drilling process (as larger wells are more costly). Moreover, knowing the basin in which the well is located allows us to define an important layer of comparison of wells, as they are more likely to face the same infrastructure and rock formation. I drop 30 observations that are not located in the United States onshore because they contain mistakes in the latitude or longitude or because they are offshore projects. I chose to drop offshore projects because they are usually more capital intensive and require specific infrastructures, although all the results remain the same when they are included.

1.3 Satellite datasets and a new flaring measure

I construct the measure of flaring using satellite data from the NASA IR public files. I rely on the approach of Elvidge et al. (2013) , which can be summarized as follows. First, a satellite pyrometer – NASA/NOAA Visible Infrared Imaging Radiometer Suite (VIIRS) – is used to measure the radiation emitted by hot sources on the earth. Then I exploit the fact that we can recover the temperature using the Max Planck equation, which relates the spectral radiance to the wavelength and the temperature of the material and the Wien's Displacement Law, which states that the wavelength of maximum spectral radiant emittance shifts to shorter wavelength as the temperature increases (Elvidge et al. (2009), Elvidge et al. (2013)).

I identify the practice of flaring using the fact that it emits at a temperature between 1600º C and 2000º C, contrary to forest fires, which generally reach about 800º C. The FracFocus data contain the longitude and latitude of each well. I use this information to investigate whether the temperature is between 1600º C

[7]For instance in the "ARPS" model, there is a stable linear relationship between the log production of the month and the log of the month.

and 2000º C at the point within 500 meters around the location point of the well. One main limitation of this dataset is that if the wells are too close to each other, then we cannot disentangle which one is flaring with a high degree of precision. Therefore, I create a variable to distinguish the cases when such a situation occurs. I validate the quality of the satellite data in several ways. First, as shown by figure A.1 the spatial detection of flaring is consistent with the geographical distribution of oil and gas basins. Second, the probability of observing a flare before the actual completion of the well is extremely low. After the well is completed, this probability surges and start decreasing, consistent with observed practices. Figure A.2 shows that we have a non-parametric probability of observing flaring equals to 3% before the well is completed; and this probability goes to 15% within the 90 days after the well completion.

1.4 Private equity in the oil and gas

Several features of the oil and gas industry make it attractive for PE capital. First, this industry is a capital-intensive sector. For instance, in 2009, the median well cost was above $4 million (Gilje and Taillard (2015)) and the average cost for a proposed onshore US gas pipeline was $7.65 million per mile in 2015-2016. Second, the oil and gas industry is risky, as the sector is highly cyclical and exposed to changes in oil and gas prices. Third, there is ample asymmetric information regarding the investment opportunity set of oil and gas companies, as it is difficult to observe the quality of reserves they have. Adverse selection is so pervasive that oil and gas firms make inefficient production decisions to prove the quality of their reserves (Gilje, Loutskina, and Murphy (2020)). The presence of risk and asymmetric information, which deter classical bank lending, and high demand of capital make the industry attractive for PE firms. Figure 1.B shows that the oil and gas industry has concentrated more than 8% of transactions for deals that imply a transfer of control rights since 2010 in the United States according to Preqin. This is quantitatively significant, as the equivalent number for the health care, insurance, or retail sector is lower. The software industry is the only industry that has a larger amount of deals in dollar value than the oil and gas industry.

I use several distinct sources to construct a database of PE deals that result in a transfer of ownership. I download all "add-on", "buyout", and "growth capital" deals and exits from Preqin that I manually match to the oil and gas dataset using the operator name. I am able to match a total of 146 deals. I cross-check the accuracy of the date of the deal, the type as well as the firm identity using both Pitchbook and Enverus market intelligence. I drop the observation if one of the source documents shows no transfer of ownership (such as mezzanine debt) or if I observe that the add-on relates to only part of the assets of the target firm and not the total assets of the firm. I also drop an observation if the acquirer is not a PE or VC firm but rather a hedge fund or other investment structure. This results in 106 firm-deal observations made by 55 different financial sponsors.

2 Net Effect Of PE Ownership On Pollution

This section studies the net impact of PE ownership on the production of toxic pollution. The identification strategy is described in subsection 2.1. The baseline results are presented in subsection 2.2 and subsection 2.3 contains a sensitivity analysis of the baseline results.

2.1 Identification strategy

2.1.1 Identification problem

PE firms' decisions are not random and depend on variables that are not always observed by the econometrician. The variables that PE firms use to decide whether or not to acquire a firm could be correlated with future pollution. Therefore, any regression of pollution on PE acquisition would be contaminated by unobserved variables that drive both the decision of PE firms to acquire the firm and the amount of pollution. Looking at the raw difference between PE firms that are not under PE ownership but will be acquired (henceforth, treated group) and the firms that are never bought by a PE (henceforth, control group) provides a first way to understand whether this selection issue is a problem. In this subsection, I provide evidence of a selection pattern concerning both PE acquisition and PE DrillCo transactions by looking at the raw differences in characteristics.

Panel A of table 3 reports the raw differences at the firm-level between our treated and control group for deals that imply a change in controls. Although quantitatively small, there is a selection problem taking place at the firm level. Our treated group is more geographically focused than the treated group: while the control group has projects on average in 1.7 states, this number is equal to 0.98 for the treated group. As a result, the treated group drills in fewer basins than the control group when there is no PE ownership. The total number of projects is statistically similar between the two groups, and on average equals 100.

Panel B of table 3 depicts the raw differences between our treated and control group at the project level, when there is a change of controls in the transaction. The differences are much more pronounced than at the firm level. Several stylized facts appeared. First, our treated group is less productive than our control group. On average, the former takes 12 days longer to drill a well. Moreover, they obtain less production for each fracturation. Second, they drill in more rural area. The wells they have are located in places with fewer housing units and persons. Third, they drill more oil and less gas than the control group. Finally, although imprecise and non-statistically significant, the treated group pollutes less: they flare less than the control group and on average they use 0.1 fewer toxic chemicals than the treated group.

If the firms in the control group and treated group drill in different locations or have projects whose characteristics are fundamentally heterogenous and not comparable, then the impact of PE firms on pollution is biased. The next subsection outlines the ways used to handle these selection problems.

2.1.2 Empirical design and identifying assumption

The key identifying assumption of this paper is that heterogeneities in the marginal costs and benefits of polluting at the project level are driven by geographical variables. In the oil and gas industry, the main source of value creation comes from constructing an acreage, which is a portfolio of lease contracts that provide the right to drill oil and gas within a specific time range and location. The type of rocks and its properties, such as its porosity and permeability, the distance from existing infrastructure (such as pipelines), which increases the cost of flaring, are similar for two wells that are located in the same area. Similarly, specific chemical suppliers in the region affect the prices and type of components sold to oil and gas operators. By comparing how oil and gas companies emit pollution facing the same marginal cost and benefit both before and after a PE deal –in a difference-in-differences setting–, we can recover whether firms tend to become cleaner following the PE acquisition.

The first way to translate in an econometric specification the identifying assumption is to estimate the following equation on the full sample:

$$Y_{ijt} = \text{Firm}_i + \text{Year}_t \times \text{Location}_j + \sum_{\tau=-6}^{10} \gamma_\tau.(\tau \text{ semester(s) after the PE deal}) + \text{Controls}_{ijt} + \varepsilon_{ijt} \qquad (1)$$

Where Y_{ijt} is a measure of pollution (toxic chemicals or flaring). Firm_i is an operator fixed effect, which captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemicals. Location_j is a geographical fixed effect and is equal to 1 for projects that are located in places with the same first two digits of latitude and longitude. Figure A.4 illustrates such grouping by plotting the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. Year_t is a year fixed effect. Controls_{ijt} include the first six months of oil and gas productions, which is a good measure of well production. I also include the vertical depth and horizontal length as additional controls to capture potential time-varying heterogeneity in the type of technology used.

The second way to translate the identifying assumption in an econometric specification is to perform a matching approach at the project level. Contrary to previous works that match firms before the buyout to another firm (following Boucly, Sraer, and Thesmar (2011)), I perform the matching both before and after the deal at the project level. Specifically, for each project of the treated group, I match a project from the control group that is made in the same basin during the same year and has the closest size (both horizontal length and vertical depth) and level of production (both six months of oil and gas production) using the Mahalanobis distance metric. Then, on this matched sample, I estimate the following equation:

$$Y_{ijt} = \text{Firm}_i + \text{Year}_t \times \text{basin}_j + \gamma.(\text{ Post PE deal})_{it} + \text{Controls}_{ijt} + \varepsilon_{ijt} \qquad (2)$$

Where $(\text{ Post PE deal})_{it}$ is a variable that takes one if the firm i at time t is under PE ownership. Controls_{ijt} include the size of the project (horizontal length and vertical depth) and its production (both six months of oil and gas production). As I have a matching sample made with the nearest neighbor matching approach, this implies that the sample size is lower. I cannot include all the fixed effects of equation (1) in this sample without dropping a significant amount of observations. As a result, I include only a firm fixed effect as well as a basin_j fixed effect interacted with a Year_t fixed effect.

2.1.3 Reliability of the empirical design

How reliable is the identifying assumption that location drives most heterogeneity in the decision to pollute? Although it is impossible to prove exogeneity, I provide in this subsection several pieces of evidence that our identifying assumption is indirectly supported by the data.

Panel B of table 3 shows the differences in characteristics between the firms without PE ownership (treated group) and the firms that are never acquired (control group) once the location-year fixed effects of equation (1) are added. The observable differences between the two groups are severely reduced and become non-statistically significant for most of them. Importantly, the adjusted differences have a lower standard deviation (except for the completion time that slightly increases). The differences between the well production per fracturation, population and housing where the well is located, its size (horizontal length and vertical depth), and gas production diminish a lot and become non statistically significant, despite a lower standard deviation of the difference. The difference in the number of toxic chemicals goes to -0.109 without fixed effects to -0.086 and the standard deviation is nearly divided by two, which implies that the difference becomes significant at a 10% level. The remaining differences in observables that are statistically significant after adding the fixed effect are the completion time and the amount of oil produced. Overall, this supports the view that wells located in the same area are a plausible counterfactual for the wells of PE-backed firms.

The dynamic difference-in-differences shows no pre-trend before the deal is signed. Figure 5 reports the pre-trend before the deal happens where the dependent variable is the number of toxic chemicals. The line is flat, slightly below 0 and the coefficients are not statistically significant. Similarly, Figure 6 contains the pre-trend coefficients for another measure of pollution, namely the practice of flaring. In this graph, the coefficients are close to 0, the line is slightly above 0, and all the coefficients are not statistically significant.

Overall, both the absence of pre-trend before the deal as well as similar characteristics in level for the control and treated group strongly support that the identifying assumption made is credible and plausibly allows us to interpret the relationship as causal.

2.2 Results

2.2.1 Raw relationship

I start the analysis by the simplest way of statistically summarizing a database: plotting the data points, as well as the fitted line, both before and after the year of a PE deal. Figure 4 shows the binscatter in red square dots. As we can see, the probability of using a toxic chemical during the production process is increasing before the year of the deal: it goes to around 0.00-0.05 one year before the deal to a peak of 0.2 the year of the deal. After the year of the deal, the mean number of toxic chemicals per project doubles to 0.4. It then starts to decrease slowly to reach the level of 0.2. The binscatter suggests that a linear specification can be used as a good parametric functional form for the econometric tests. The raw relationship suggests that PE ownership is associated with an increase in toxic pollution that decreases slowly before the exit.

The increase in pollution that is associated with PE ownership is not causal, as they are strongly exposed to a composition effect. The type of projects used by PE-backed firms changes following the acquisition. Figure 4 contains in blue dots the binscatter of the control projects from the matching sample[8] and is a direct way to correct for this composition effect. We observe a visual common trend before the year of the deal. Two to three years after the deal, the production of toxic chemicals still increases for our control group, while it decreases for the group of PE-backed firms, highlighting a negative impact of PE ownership on pollution.

[8]To recall, we construct the matched sample by matching for each project of our treated group a project from the control group that match a project that is made in the same basin during the same year and that has the closest size (both horizontal length and vertical depth) and production level (both 6 months of oil and gas production) using the mahalanobis distance metric.

As the binscatter ignores time-unvarying shocks and geographical-specific trends as well as standard errors, the next part of the paper examines the relationship by exploiting the full panel dimension of the dataset by adding fixed effects.

2.2.2 Difference-in-differences

Figure 5 reports the estimated $(\gamma_\tau)_{\tau=-6,\ldots,4,10}$ of equation (1) and confirms the negative relationship between PE ownership and pollution. While all the post-deal estimates are statistically significant at a 5% level (except for the sixth semester after the deal, which is significant at the 10% level), none of them are before the deal. There is no visual and significant pre-trend after the PE deal. We can observe a small but non-significant drop in the number of toxic chemicals used after the year of the deal. The negative impact of PE ownership is stronger with time. After the first three years, the number of toxic chemicals is reduced by 0.4. As can be seen in table 2, the sample standard error of the number of toxic chemicals used during the production process is .55. Therefore, the reduction in pollution is economically meaningful, corresponding to a drop of more than half of the standard error. None of the coefficients of the controls are significant and the point estimates are economically non-significant (below the 10^{-6} level), which is an indication that all the observed heterogeneity between projects and potentially correlated with proxies of productivity and technology have already been controlled with the fixed effects.

Table 6 contains the net post effects. Both columns (1) and (2) of Panel A show that PE ownership leads to a mean average effect of -0.198, which is economically and statistically significant. The sample mean of toxic chemicals used is 0.282. As a result, a reduction of -0.198 implies that the drop is equivalent to 70% of the baseline usage of toxic chemicals. Column (3) of Panel A contains the net effect using the matching approach of equation (2). Although the sample and fixed effects are different, the magnitudes are close, the effect of PE ownership using this specification is equal to -0.209.

I estimate the baseline equation (1) with a different measure of pollution, flaring. Figure 6 contains the plot of the dynamic effect around the deal estimated on the sample where we can unambiguously identify the identity of the owner of the well, that is when the wells are not too close to one another. Similar to the results using toxic chemicals, we can observe a drop in pollution coming from the practice of flaring. Most of the decrease in flaring comes after year three, where PE ownership plausibly causes a drop by 10% in the probability of flaring. This is quantitatively significant, as the standard deviation in the practice of flaring is equal to 0.16. Columns (1), (2), and (3) of Panel B from table 6 report the full post-deal effect of PE ownership on flaring. The overall net effect of PE ownership is negative, equals to -0.044, and stable to the inclusion of controls as well as statistically significant. Moreover, when estimated on the matched sample, we find magnitudes that are close to the results using the full sample.

2.3 Sensitivity analysis

I replicate the baseline specification where I drop projects that are in locations that account for a large fraction of the firm total projects. PE firms' purchase decisions are based on variables that are mostly driven by the main basin(s) where firms operate. The extreme case would be a situation where a PE firm purchases a target company by only considering its core assets. If the PE firm reduces pollution on all the projects of the target company, then dropping these core assets and focusing the analysis on the other wells would alleviate the endogeneity problem. By dropping these basins in the analysis, we are more likely to focus our attention on places that are not driving the decision of the PE to purchase the company.

To perform such a test, let's define $C=\frac{\text{Number of projects in basin j for firm i}}{\text{Total number of projects for firm i}}$. Table A.2 of Panel A reports the baseline regressions where I drop firms that have a C that is higher than a specific threshold. Specifically, in column (1) I drop all the projects where C=1, which consists of dropping firms that are drilling in only one basin. The effect on this sample is equal to -0.183, close to the -0.198 found in the baseline specification. Columns (2), (3), and (4) estimate the relationship where C is below 0.77 (75th percentile), 0.21 (median), and 0.11 (25th percentile). Although the baseline equation is estimated on different samples, the effects are within the same magnitude range and are equal to -0.174, -0.268, and -0.162 for columns (2), (3), and (4) respectively. Overall, this exercise suggests that the baseline results are robust and resist when we drop the assets within the firm that are more likely to cause PE firms to purchase.

Next, I focus the analysis on projects that account for a small fraction of the total number of projects in the basin. Suppose a firm owns a large fraction of projects within a location. This results in a higher ability to negotiate the cost of inputs used as well as other costs that could change the project-level marginal cost and benefit of using toxic chemicals. To handle this concern, I first define the following ratio $M = \frac{\text{Number of projects in basin j for firm i}}{\text{Total number of projects in basin j}}$. M is equal to 1 implies that the firm produces all the wells in the basin. Table A.2 of Panel B reports the baseline regressions where I drop firms that have an M that is higher than a specific threshold. No firm has all the projects in one location. Columns (1), (2), and (3) drop if M is respectively higher than 0.085 (75th percentile), 0.046 (median), and 0.01 (25th percentile). The coefficients for columns (1), (2), and (3) are equal to -0.198 -0.219 and -0.297. These coefficients imply an effect similar to the baseline magnitude, if not more important. These tests suggest that the effect is not driven by differential local bargaining powers correlated with PE ownership.

Overall, the results are consistent with a reduction in pollution following PE acquisitions that is plausibly causal. The remaining of the paper studies several channels that could explain this reduction.

3 Financial Constraints And Drillco Contracts

PE firms could lead to lower pollution by reducing a financial constraint. Financial constraints affect pollution if investment in abatement technology projects create NPV value. A high cost of capital or the inability to borrow could prevent the firm from making such investment in abatement projects. PE sponsors are deep pocket investors, that typically have existing funds with undrawn capital (Gompers, Kaplan, and Mukharlyamov (2016)) and are more likely to inject capital to their firms in case of financial distress (Hotchkiss, Strömberg, and Smith (2014)). If financial constraints were the main channel through which PE firms reduce the pollution of their portfolio company, then we should also observe a reduction when PE firms only provide financing to companies, even if they don't control the management team. The goal of this section is to exploit the existence of Drillco contracts in the oil and gas industry that are a contract through which PE firms only provide financing to a company.

3.1 Drillco contracts

DrillCo are a joint venture between a financial investor and an exploration and production (E&P) company. They do not imply the creation of a new firm, contrary to what the name suggests. There is a large variety of DrillCo contracts and their features are only limited by the creativity of the contracting parties. In its basic form, a DrillCo is a contract where an investor provides cash in exchange for a working interest in a group of wells that are drilled and operated by the E&P company. Most of the time, a DrillCo contract contains three main components. In each tranche[9], the investor provides a capital commitment. This capital commitment is used to pay the development costs of the well(s) and part of the E&P working interests as a form of a carry ("carried amount"). In exchange for the capital commitment, the investors acquire a working interest in each tranche. This working interest can be subject to partial reversion once pre-determined IRR hurdles are met. More complexity of the DrillCo contracts can then be found. The location of the acreage can be made confidential to avoid potential competitors to compete directly with the firm. The DrillCo contract can also contain an alternative plan in case the initial wells are dry hole. The working interest is defined at the wellbore, but can be depth limited. Another important source of heterogeneity in DrillCo contracts is

[9] A tranche is a group of oil and gas wells

the timing of the payment, regarding both the moment when the investor transfers the funds and when the operator pays back the investors. The development costs of the well(s) can have a specific limit or for some deals a budget can be agreed upon.

DrillCo transactions differ in several ways from a traditional PE acquisition. They imply less control from the investors than when an acquisition is made. Most of the operational decisions are undertaken by the E&P company. As Tim Murray from Benefit Street Partners[10] explained: "We don't micro-manage operational details about how you're fracking the wells". Another difference is that there is no change in capital structure, contrary to what happens in a leveraged buyout. Finally, in a DrillCo all the income made by PE investors comes from the working interest in a tranche of wells, and does not come from the exit value of the deal. Therefore, DrillCo contracts are interesting because they are financing from PE funds but without any transfers of control rights, change in capital structure, and pressure to exit the investment.

I obtain DrillCo deals through a new data provider, Enverus market intelligence. The data provide 30 DrillCo contracts with precise information on which area are subject to a DrillCo deal as well as the name of the capital provider. For 20 firms, I observe that a DrillCo has been signed and in which basin the contract area is, but I don't have the precise shapefiles.

3.2 Descriptive statistics and balance tests pre-Drillco

Panel A of table 4 reports the raw differences between firms that signed a DrillCo deals and the other firms, before such a transaction occurs. Firms that sign a DrillCo are on average bigger, they have 387 projects whereas the control firm has only 89 projects. As a result of having more projects, firms that will sign a DrillCo are drilling in more places and states. However, these differences are not statistically different, except for the number of coarser locations that is significant at the 90% threshold.

Panel B of table 4 reports the raw differences for a DrillCo transaction using project-level information. There are differences between the firms that sign a DrillCo deal and the others. The raw differences are economically important for most of them but imprecise and exhibit a large standard deviation. These differences are thus non-significant except for the production of gas that is significant at the 10% level. The average firm signing a DrillCo transaction uses slightly more toxic components, is less productive and efficient as captured by the completion time and the production per fracturation but uses more technological advanced projects as measured by the vertical depth and horizontal length of the projects.

Panel B of table 4 shows the differences in characteristics between firms before they signed a DrillCo and the others, once the location controls are added, which also supports the identifying assumption. Most

[10] In "The DrillCo" by Nissa Darbonne in Oil and Gas Investor, Money Redefined: capital Formation, June 2016

of the differences in absolute terms are strongly diminished between the two groups after the location is taken into account. For instance, the difference in production per fracturation goes from -16 to -2.44 after such controls are added. The difference in the production of oil for the first six months goes from -4,759 to 2,627. The first six month of gas production shows significant differences from a statistical point of view at the 90% confidence intervals but this difference is strongly reduced in absolute terms once the location fixed effects are added, as they go from 65,086 to 10,744. The last variable that has a difference that is statistically significant is the horizontal length of the well. The magnitudes are small as the difference is equal to less than 2.5% of an average project but precise, with a standard deviation of the difference that goes from 554 to 86 after the controls are added. Overall, these differences support the view that wells located in the same area are also a plausible counterfactual for the wells of firms that signed a DrillCo.

3.3 Results and interpretation

I adopt a specification similar to equation (1) to investigate the impact of PE financing on pollution. Figure 9 reports the estimated $(\gamma_\tau)_{\tau=-6,\dots,4,10}$ of equation (1) when the deal variable is for DrillCo transactions and the dependent variable is the number of toxic chemicals. There is no pre-trend before the Drillco contract is signed and it is difficult to observe an effect after.

The absence of a statistically significant effect following a drillco transaction is confirmed using different specifications and measures of pollution. Equations (4) to (6) of Panel A from table 6 contains the net post effects for drillco contracts on the number of toxic chemicals. The point estimate is small in magnitude, around -0.03, close to 0 and statistically non-significant at conventional thresholds. Equations (4) to (6) of Panel B from table 6 report the estimate when the dependent variable is flaring following drillco contracts. Similarly, the point estimate is close to 0 and statistically non-significant.

Overall, this test brings evidence that reducing pollution is not caused by a lack of financing for positive NPV project. The reason for why this is the case is that the signature of a DrillCo contract is a positive wealth shock for a firm. Financing a set of projects through a DrillCo preserves the cash reserves and the debt capacity of the firm. A firm with more financing capacity can invest in other positive NPV projects. A positive NPV project could be an investment in abatement technology with a high payback period. If a financial constraint is hindering the manager to invest in such project, then we should also observe a drop in pollution when the constraint becomes less binding following a DrillCo contract, which is not what we observe. This non-result implies that corporate executives face specific incentives not to invest in pollution abatement projects and that such incentives are affected when PE firms control the management team. Understanding these incentives is the focus of the next section.

4 The Role Of PE Monitoring

In this section I investigate whether the reduction in pollution that we observe is consistent with better monitoring of managers by PE sponsors. Managers with better monitoring will decrease pollution when it maximizes shareholder value. A PE sponsor provides a form of ownership that better aligns the incentives of owners with the corporate managers (Morris and Phalippou (2020), Gompers, Kaplan, and Mukharlyamov (2016)). The use of greater debt disciplines managers, and PE firms increase managerial incentives to maximize profit through performance pays. General partners, on behalf of limited partners, control the board of their portfolio companies and actively monitor them. In this section, I provide several tests that bring support for this channel.

4.1 Cash flow structure

Agency frictions create an incentive for managers to artificially boost short-term earnings at the expense of long-term shareholder value, as short-term earnings are used as a signal for future performance by external financial investors (Stein (1989), Grenadier and Malenko (2011)). Does increasing pollution boost short-term earnings? Large sample data on discount rates in the fracking industry are difficult to obtain without making assumptions on the costs of projects[11]. To solve this problem, I study and discuss in this section the cash flows and costs structure of flaring.

Most of the cost of reducing flaring is paid at the beginning of the project. It consists of connecting the well to a pipeline and has two components. On-site facilities and equipment, such as dehydrators and compressors need to be installed close to the well. Their prices vary greatly according to the location and the year, so precise project-level estimates are hard to come by. According to the Interstate Natural Gas Association of America (INGAA) the costs were on average $210,000 per well in the Bakken. Then, the well needs to be connected to a pipeline and the price is a function of how far the well is to a pipeline and the diameter of the connecting facility. According to the INGAA, the prices in 2017 ranged from $29,000 to $167,000 per mile for a diameter range between 2 and 22 inches.

[11] See Décaire (2019) for a paper developing a methodology to estimate the realized costs and cash flow of wells in the conventional natural gas sector.

The cash flows follow a predictably declining curve. Production of gas flared is available for North Dakota, but information on whether the well is connected to a pipeline is not available. Focusing on projects that are most likely not to have been connected to a well, Figure 7 plots the production of gas for each year after the well starts producing. As can be seen and consistent with an ARPS model used by practitioners (Fetkovich (1980)), we have a convex declining curve of gas production. Half of all the gas flared during the first 15 years of the life of a well is done within the first year and a half.

Given these costs and cash flows structure, a manager that wants to boost short-term profits would not connect a well to a pipeline, because it avoids the upfront costs and the lost in profit is diffuse in time. As shown in Table 6, flaring is strongly reduced following a PE acquisition, which is consistent with the view that PE ownership leads the firm to adopt long-term environmental policies following the reduction of asymmetric information between managers and owners.

4.2 Shock to regulatory risk: a natural experiment

If PE firms are an owner that better monitors the executive managers of the firms, then we should expect a reduction in pollution that is less important when the pecuniary incentive to do so is lower. In this subsection, I exploit a natural experiment that provides plausibly exogenous shocks in the future regulatory cost of polluting to study whether the reduction in pollution becomes lower for firms with PE ownership.

4.2.1 Institutional background

The Bureau of Land Management (BLM) is responsible for the environmental regulation of federal land and Native American reservations. It oversees one eighth of the land in the continental United States. It is a federal agency within the U.S. Department of the Interior. Its core mission is "to sustain the health, diversity, and productivity of the public lands for the use and enjoyment of present and future generations." Within its mission, the BLM supervises the leasing of oil and gas reserves and provides technical advice for drilling operations on Native American reservations.

In 2012, the BLM started drafting a regulation aimed at reducing the negative externalities caused by hydraulic fracturing. The rule was finalized and made available on March 26, 2015 after collecting feedback, remarks, and comments. The regulation was supposed to be effective on June 24, 2015. It comprised several points: (1) improve the disclosure of operational activities, (2) increase the quality and integrity of the wellbore, and (3) increase the standard of water protection. This rule did not forbid the usage of highly toxic chemicals, but increased their indirect costs. Specifically, operators were required to "isolate all usable water and other mineral-bearing formations and protect them from contamination." The rule expanded the definition of usable water to include "waters containing up to 10,000 parts per million (ppm) of total dissolved solids," which doubled the previous threshold.

On March 20, 2015, various petitioners filed a motion for preliminary injunction to challenge the fracking rule[12]. The preliminary injunction was granted by the Federal Court of the 10th Circuit. The Federal Court found that "BLM did not have the authority to regulate fracking" (Williams (2015)), ending uncertainty over whether the BLM had legislative power over fracking activities. Specifically, each of the acts used by the BLM to justify its right to enact the Fracking rule, such as the Federal Land Policy and Management Act ("FLPMA"), the Mineral Leasing Act ("MLA") , was rejected by the court, under the reason that "none of them gave BLM authority to regulate fracking" (Williams (2015))[13].

Figure 7 reports the main milestones of the subsequent court proceedings. On June 21, 2016, the rule is abrogated by the District of Wyoming and three days after the BLM appealed. On January 20, 2017, Trump is inaugurated and proceed to a change in the political orientation of the BLM, which now no longer supports the fracking rule. An interior Department Assistant Secretary stated that an "initial review has revealed that the 2015 Rule does not reflect . . . the current Administration's policies and priorities concerning the regulation of hydraulic fracturing on Federal and Indian lands". Shortly after, the Trump administration issued an executive order asking for the BLM to rescind the rule[14]. This causes the Tenth Circuit to dismiss the lawsuit as moot on September 21, 2017. The rescind is made official on December 29, 2017.

Following this rescind, the State of California and a group of environmental activists sue the BLM on January 24, 2018 for voiding the fracking rule. Three main reasons were put forward to justify such an action. Firstly, this decision of the BLM was accused to be capricious. The Administrative Procedure Act (henceforth, APA) requires that any agency that decides to change its policy should explain why the new policy is better. The rescind was motivated by the fact that it was supposed to promote energy development on federal and tribal lands by removing regulatory burden. However, this explanation was not supported by the evidence put forward by the BLM itself that finds that the price of oil and gas is the main factor affecting the production of fracking activities. Thus the explanation "runs counter to the evidence before

[12]The petitioners included the Independent Petroleum Association of America ("IPAA"), the Western Energy Alliance ("Alliance"), the states of Utah, North Dakota, Wyoming, Colorado and the Ute Indian Tribe.

[13]The remaining reasons to grant the preliminary injunction were the following. First, the regulation was not supported by "substantial evidence and lacked rational justification". Second, the consultation meetings with indigenous American tribes were not made in a way consistent with procedures and policies that this regulatory authority should respect. The next two reasons stated that the petitioners would have incurred "irreparable harm" if the regulation was allowed while the litigations were pending and these costs outweighs any potential harm to BLM.

[14]Executive Order No. 13,783, Presidential Executive Order on Promoting Energy Independence and Economic Growth, 82 Fed. Reg. 16,093 (Mar. 28, 2017).

the agency". Secondly, the APA requires that agencies should always act in a way that is allowed by their statute. The rescind of the fracking rule was seen as contradicting its statute. Indeed, the core missions of the BLM are to prevent "unnecessary or undue degradation" of public lands and to enable the development of energy while ensuring environmental protections. Thirdly, the decision to rescind the rule violates the National Environmental Policy Act as the BLM didn't carry out an environmental impact analysis of the repeal.

4.2.2 Descriptive statistics between projects in Native American reservations / federal lands and the others

It is important to investigate whether the projects that are drilled in Native American reservations and federal lands are similar to the others before the fracking rule is announced in March 2015. One concern would be that the way contracts are enforced[15] or local labor cost create fundamental differences between the projects of the two groups that command different usages of toxic pollutants, making causal inference difficult to obtain.

Panel A of table 5 shows the raw differences between the two groups before March 2015. Pollution is higher in Native American reservations and federal lands, as captured by both the number of toxic chemicals and flaring. This group is also less productive, as captured by the completion time and the production per fracturation, and produces fewer oil and gas per well. Projects have a lower horizontal length outside federal lands and Native American reservations. Although statistically non-significant, projects in Native American reservations and federal lands are also located in places that have a lower population density.

Once the location fixed effects are added, most of the differences in characteristics are reduced by an important magnitude and becomes all non-statistically significant at the 5% threshold. This is consistent with the idea that location is an important driver in the heterogeneity of projects. Specifically, the differences in the production of oil goes from 2,015 to 43,47 BO, which is a division by 46 and the production of gas is strongly reduced, divided by 17. Both differences are non-statistically significant. The differences in the size and length of wells become economically and statistically non-significant. The only remaining statistically significant differences are for variables on productivity and population density, if we set a confidence interval of 90%. The economic magnitudes are however non-significant: for instance, projects take one day

[15] Brown, Cookson, and Heimer (2017) and Brown, Cookson, and Heimer (2019) exploit the 1953 enactment of PL280 that creates plausibly exogenous variations in the enforcement of contracts within Native American reservations, where litigations were enforced following the shock on state courts instead of tribal courts for some reservations and show that it affects credit markets, income, financial literacy and trust. The shocks that are exploited in this study are different and exploit the regulatory power that the BLM has to intervene on Native American reservations and federal lands on environmental matters. It is a shock on the *ex ante* ability to regulate fracking rather than a shock on the enforcement of contracts.

more in Native American reservations and federal lands to be completed or contain seven fewer persons per county. Overall, these adjusted differences suggest that projects in their vicinity have similar characteristics that are not affected by the fact that they are regulated or not by the BLM before March 2015.

4.2.3 Empirical specification

The timeline of events suggests that over the period of March 2015 to January 2018, projects drilled on federal land and Native American reservations were subject to a lower amount of environmental regulation risks, as evidenced by the preliminary injunction in 2015, the court decision against the fracking rule in 2016, the Trump inauguration, and the subsequent shelving of the fracking rule, which all create important hurdles regarding the ability of the BLM to regulate fracking. I exploit these factors in the identification strategy. Specifically, I estimate the following equation:

$$Y_{ijt} = \text{Firm}_i \times \text{Year}_t + \text{Location}_j \times \text{Year}_t + \sum_{\tau=2012}^{2019} (\text{year}=\tau) \times (\text{BLM})_i \times (\gamma_\tau + \beta_\tau.\text{PE}_{it}) + X_{it} + \varepsilon_{ijt} \qquad (3)$$

Where $(\text{BLM})_i$ is a variable that takes one if the well is located on federal lands or Native American reservations. The fixed-effect specification is similar to the one used before in equation (1). The coefficients allow the differences to vary with time to capture potentially dynamic effects. The inclusion of firm fixed effects interacted with a year fixed effect is a notable empirical advantage of the oil and gas empirical setting. In particular, it allows us to absorb any time varying firm-level unobserved variables that drive the decision to use toxic chemicals. These unobserved factors are usually the one driving the decision of PE firms to purchase a firm. The specification allows us to compare projects drilled in the same year by the same firm in the same rock formation, where they differ because one is located in a federal land or a Native American reservation, whereas the other is not. Then this effect is decomposed between the impact of the regulation by non-PE backed firms, captured by γ_τ and the one driven by PE-backed firms, measured by β_τ.

4.2.4 Results

Figure A.7 plots the estimated coefficients $(\beta_\tau)_{\tau=2012,...,2019}$ of equation (3). We can observe a jump after 2015 in the usage of toxic chemicals for projects located in areas supervised by BLM and for PE-backed firms. After the preliminary injunction is granted, PE-backed firms start to use more toxic chemicals in their wells than the other firms, but this difference disappears after 2018. After 2018, the effect is economically and statistically small, consistent with the fact that the state of California's decision to sue the BLM created an increase in the probability of having a fracking rule. The effect is higher in 2017, the year when Trump is elected and the rule is rescinded.

Table 8 contains different variations of equation (3). Panel A reports the full interaction in a triple difference-in-differences setting. The variable Post Injunction takes a value equal to one after the preliminary injunction and 0 before January 2018, the moment when BLM is sued for having rescinded the rule. Columns (1) and (2) estimate the full interactions with separate firm fixed effects and location-year fixed effects. Controls are added in column (2), and column (1) contains the results without any project-level controls. The triple interaction coefficients between PE ownership, BLM, and post injunction are similar, statistically and economically significant. They are equal to 0.38. Columns (3) and (4) of Panel A report the coefficients when firm-year fixed effect are added. Likewise, the triple interaction coefficients are statistically and economically significant and equal to 0.3, which is equivalent to the average sample use of toxic components for a firm in the sample. Finally, Panel B reports the net effect, that is when only the triple interaction coefficient is specified without the other interactions. The coefficients remain stable and similar in magnitude to the results found in Panel A.

PE-backed firms reduce pollution less when the cost of polluting are higher, because it maximizes expected future shareholders value to do so.

4.2.5 Discussion

PE-backed firms reduce pollution less following lower regulation risks, which allows us to rule out a channel driven entirely by non-pecuniary motives, unless there are agency frictions between limited and general partners. Limited partners could have a preference for socially responsible investments and ask the general partners to invest accordingly. Standard models of moral hazard dictate that optimal effort should be exerted in states of the world where the signal is more informative about the agent's efforts. A litigation with federal agencies is a strong signal that the general partners polluted and did not adopt high environmental standards. As a result, the general partners will exert more effort –in our setting, pollute less– when the precision of the signal is higher; that is, when polluting can lead to litigation and fines with federal agencies, which is precisely what happens when the fracking rule was discussed and was about to be implemented. This interpretation is however unlikely, as we are using information that is also available to the limited partners and could be used to monitor the general partner.

A way to explain the existence of non-pecuniary preferences among corporations and investors is to suppose the existence of frictions that prevent governments from implementing a regulatory framework consistent with social preferences (Bénabou and Tirole (2010)). For instance, if voting or representative democracy are limited in creating a legal environment that maximizes citizen welfare, then the for-profit world can take a role of realizing social preferences by taking non-profit actions. According to these theories, the BLM litigations can be thought of as a case where the government lacks the tools to implement social preferences. Therefore, if the results were driven by ESG motivations explained by this channel, then we should observe a decrease in pollution instead of an increase when regulatory risks become less important.

This result is not consistent with the idea that the reduction is driven by a technological upgrade. For this to be the case, we would have to assume a technological innovation that is worth using in Native American reservations and federal land between 2015 and 2018 but not in the wells in their vicinity. Moreover, the inclusion of controls that strongly correlates with technological upgrade in this industry, namely the total amount of production extracted as well as the size of the wells, does not affect the parameter of interests. This also implies that the technological innovation shouldn't alter these variables in an important manner. Overall, these results put important hurdles on the view that the effects are driven by a technological change inside the firm following the PE acquisition.

4.3 Agency frictions within publicly listed firms

If Private equity ownership reduces pollution because they closely monitor their portfolio companies, then it implies that agency frictions matter for pollution. I provide additional evidence of the role of agency frictions in the decision to pollute by looking at publicly listed companies. Bertrand and Mullainathan (2001) and Davis and Hausman (2020) suggest that shareholders from public listed companies in the oil and gas industries do not perfectly monitor their corporate executives and are thus able to extract a rent by being paid for outcomes not tied to their efforts. Agency frictions could create incentives to to boost short-term performance, potentially at the expense of long-term performances as in Stein (1989) and Grenadier and Malenko (2011). One of them could be to use more toxic chemicals.

To test this channel, I begin by investigating whether public listing is associated with more toxic polluting using the same identification idea as for the PE ownership tests, that relies on comparing projects that are close geographically, both before and after the IPO. One caveat is the small number of oil and gas IPO between 2010 and 2019. With this caveat in mind, I exploit six IPOs that take place during my sample period and replicate the geographical fixed effect specification used in the previous section. Panel A of Table A.9 shows that the production of toxic chemicals increases following the IPO in a significant manner. The magnitude of the effect of IPO on pollution is an increase of 0.14, which is close in absolute terms to the reduction (-0.19) caused by PE ownership. One limitation of this specification is that it relies on a small number of firms.

I next show that firms missing the mean forecast of their annual earnings per share (henceforth, EPS) are more likely to increase pollution, which is consistent with the view that financial markets expectations create short-term pressure leading to more pollution. Firms that have the highest marginal gain to increase their one-year EPS, namely the firms that have a realized EPS that is far below the expected one, should take inefficient actions such as over using toxic pollution, to boost their EPS. This prediction is supported in the data. Specifically, figure A.8 reports the estimates of a regression of toxic pollution on the nine deciles of the sample EPS forecasts' errors, after adding the geographical-year and firm fixed effect as well as controlling for the realized EPS. Being among the first two deciles of the errors on EPS, which means having the 20% lowest differences between the expected EPS and realized one, leads to an increase of pollution of 0.1, which is half of the absolute magnitude of the effect of PE ownership and close to the effect of public listing. In contrast, all the other deciles are not associated with an economically and statistically significant effect on pollution, except for the highest decile (q9). Equation (4) and (5) of table A.9 confirm the effect of EPS on toxic pollution in different specifications and show that the relationship holds when the company has a realized EPS that is below the one expected by financial analysts.

5 The role of the Incentive To Exit In Private Transactions

Reducing pollution also maximizes the PE value through a higher selling price of the portfolio company. PE firms have an investment horizon of five to ten years on average, which implies that they care more about the exit price than shareholders with a longer holding time. Selling a polluted asset is difficult because they expose the new owner to more environmental liability risks. Environmental liability encompasses any environmental cost associated with the asset, such as current and future compliance costs, cleanup costs implied by the releases of hazardous substances and any potential fines and litigation fees caused by environmental torts or trespass. It is difficult to know precisely the amount of environmental liability an asset contains and gathering information is costly. Potential buyers have different beliefs and information regarding the distribution of these risks. This creates a discount for assets that are polluted. If the selling price of an asset is lower than the risk-adjusted discounted value of its cash flow when the asset contains pollution, then it becomes optimal for an owner aiming to sell such an asset to make it cleaner. This behavior is consistent with economic models of product differentiation (Osborne and Pitchik (1987)), where there is a benefit to changing the amount of characteristic (pollution) to either increase the demand for a good (the portfolio company) or attract buyers with a higher valuation for that characteristic, who are thus willing to pay a higher price.

5.1 Trading discount of polluted asset

One direct prediction of the exit pressure channel is that polluted assets are sold at a negative price, holding their fundamental values constant. In this subsection, I use a new database of 987 transactions from Enverus to understand whether wells that use toxic chemicals are sold with a discount in private transactions.

I lack a quasi-experimental setting to test the relationship between toxic pollution and the price at which assets are sold. Ideally, we would like to exploit random variations that affect both the decision to sell an asset as well as the decision to pollute. However, I exploit a dataset that contains a large amount of detailed information on assets sold in the onshore U.S. oil and gas industry and the quality and precision of the variables I observe enable us to control for potential omitted forces at a high degree of granularity that is usually not possible to meet in other empirical settings. The quality of the controls that are added puts several hurdles on alternative explanations regarding the relationship between the price at which the assets are sold and the usage of toxic pollution. For each transaction I observe the amount of proven reserve that is a key variable when evaluating the potential of an acreage. I observe variables of production and the basin where the projects are located. Moreover, I observe the price at which the transaction happens as well as the identity of the sellers and buyers.

There is an important negative relationship between the price at which projects are sold and the usage of toxic chemicals, that remains stable and robust following the inclusion of controls. Figure 11 plots the raw relationship between pollution and the price of the transaction. As we can observe the correlation between the price at which a polluted asset is sold is negative and statistically significant. The correlation is equal to -0.2708 and is significant at the 1% level. Table A.10 reports the impact of toxic pollution on transaction prices by slowly adding different controls. Specifically, column (1) estimates the relationship in a regression without controls. Column (2) adds project-level and asset-level controls. Next, columns (3) to (6) report the regression coefficient when fixed effects are added. Column (3) starts by adding a fixed effect for the type of transaction (acreage or corporate assets for instance). Column (4) adds to the previous column the location fixed effect and column (5) a basin fixed effect. The coefficient of interest for all regressions is between -0.417 to 0.249 and is statistically significant. Finally, column (6) adds a buyer and seller fixed effect. This leads to a drop in the sample size (193 transactions instead of 987), as we restrict the analysis to firms that trade several times during the sample frame. However, the coefficient remains similar in magnitude,

-0.466, although the standard errors become much larger. Overall, the results show that we obtain a negative relationship between polluted assets and the price at which they are sold.

6 Identification Threats

In this section I address two plausible identification threats: (1) A composition effect not captured by the fixed effects, (2) an effect driven by strategic reporting where PE firms report a toxic component as a confidential item instead of not using the toxic component. Finally, I replicate the results with another definition of toxicity.

6.1 Endogenous sorting on population and housing density

One potential concern is that PE firms could drill in places with a higher population or more housing units. This would imply that PE firms increase the human exposure to pollution, despite reducing their production. The fixed-effect specification partially mitigates this concern by having a level of geographical comparison that is coarse, namely a square of 6 by 6 miles. However, there could still be population variation within these locations. This section shows that wells drilled by PE-backed firms are not located in census tracts with a higher population or more housing units and that controlling for these factors has no impact on the final results.

The first test is to adopt a specification similar to both the baseline results and the natural experiment where the dependent variable is the total population of the census tract or the number of housing units where the well is located. Panel A of table A.7 contains the results for the baseline effects. The magnitudes are economically small: PE-backed firms drill in areas that have at most less than two housing units or less than one person and the effect is not statistically significant at the 5% threshold. Panel B of table A.7 shows the results for the natural experiment. Similarly, the magnitudes are not economically and statistically significant. Specifically, after the BLM shock, PE-backed firms drill in areas that have at most less than four housing units or nine persons. Overall, the specifications suggest that the results are not driven by a composition effect where PE-backed firms compensate the reduction of pollution by drilling in areas with a higher population or housing density.

The second exercise is to replicate the baseline tests and the natural experiment where the housing and dependent variables are added as controls. Table A.5 contains the results for the baseline specifications and table A.6 for the natural experiment. The controls are added in a linear way. Then, the controls are added as well as their squared value with their full interactions, to capture potential non-linearity effects. Finally, I create a sample decile for the number of housing units or the total population of the census tract where the well is located and add it in the specifications as a fixed effect. Overall, the results remain similar when such controls are added.

6.2 Role of strategic reporting or green washing

The next verification consists in testing whether the observed drop in toxic pollution is driven by firms reporting toxic components as confidential. This could be a concern as firms can report a component as a trade secret instead of providing its specific CAS number. PE-backed firms could simply be better at manipulating state disclosure.

The first test is to replace the dependent variable as the number of confidential items that is reported, in both the baseline results and the natural experiment specification. Table A.4 contains the results. Panel A shows that both PE ownership and financing through DrillCo contracts are associated with an improvement in the reporting quality, as they lead to an important drop in the number of confidential items reported, which is both economically and statistically significant. Specifically, PE ownership and financing leads to a drop of four confidential items reported. Panel B shows that the BLM shock has no significant impact on the number of confidential items reported. The magnitudes are not statistically significant and small, below one item.

The second test is to add as a control the number of confidential items reported. If the effect is driven by a substitution effect, then the drop in the number of toxic chemicals should be absorbed by the control. Table A.3 reports the results of this exercise. The controls are first added in a linear way or as a fixed effect for each number of confidential items. The baseline magnitudes are similar for both the natural experiment and the baseline effect.

Overall, these two tests suggest that the effects are not driven by a strategic reporting motive, where PE-backed firms report their toxic chemicals as confidential items.

6.3 Other measure of toxic chemicals and geographical distance

In appendix A.8 I replicate the results with another definition of toxic chemicals. I use the EPA's Integrated Risk Information System (IRIS) instead of congressional reports. While the IRIS classification is noisier and contains components that are not proven to be toxic by scientific papers and aggregate different levels of toxicity, the results are qualitatively the same. Panel A shows that PE ownership leads to a drop in pollution. The magnitudes are lower, as the effect is equal to -0.089 instead of 0.19. The effect is statistically significant. Similar to the baseline results, we find a small and statistically non-significant effect of DrillCo deals on pollution. Panel B confirms the results of the natural experiment, that PE-backed firms pollute more following an increase in regulatory risks. Consistent with the idea that this measure is noisier, the magnitudes are lower and equal to 0.17 but are statistically significant.

I estimate different variants of the baseline results to ensure that the main results are not entirely driven by how the econometrician groups the wells together. Specifically, I estimate the dynamic event-study windows with a new set of fixed effects. I include a geographical-time fixed effect, that regroups within the same year, wells that are in the same basin, the same state as well as the same latitude and longitude unit. Figure A.5 maps the different regions that are used to construct the same latitude and longitude unit. The results can be seen in Figure A.6 and are similar to the baseline estimation.

7 Conclusion

This paper shows that PE creates an important decrease in the production of pollution in the oil and gas industry. The reduction is statistically and economically significant. Both the emissions of CO2 and the release of toxic chemicals are reduced.

Why do PE firms reduce the pollution of their target firm? Far from pure altruistic motives, this paper shows that the reduction is explained by two economic mechanisms. First, better corporate governance following the PE acquisition leads to a reduction in pollution when it maximizes long-term shareholder value, such as in energy abatement projects with high payback periods. Second, the reduction in pollution is driven by an incentive to increase the selling price of the portfolio company. Potential buyers have different ways to value polluted assets as the environmental liability risk they expose is not perfectly observed. Making the asset cleaner either enable the PE to attract more buyers, thus pushing the price up, or extract more surplus from buyers that have a higher valuation for cleaner asset.

This reduction is conditional on production happening with a given technology and geological basins. This study is silent on any possible general equilibrium effects of PE financing on the total amount of pollution that this sector generates. Measuring such impact at the industry level is not in the scope of this study, as it would require knowing (1) how the financing provided by PE can be substituted by other source of funds (2) how the lack of PE financing delays production and (3) how exogenous technological progress in the oil and gas affects pollution. Moreover, this study is silent about cross-industry effects. Acemoglu et al. (2019) highlight that shale gas activities can also have general equilibrium accross industries. If shale activities reduce the usage of coal that is more CO2 intensive, it also increases the pollution by increasing total output and by reducing the incentive to innovate in clean energy.

Initiatives to decarbonize portfolios could come at the cost of increasing pollution in dirty industries. Active investors, such as PE firms, reduce pollution in industries that are considered as "dirty," such as in the oil and gas. If limited partners of these PE firms decarbonize their portfolios[16], this could reduce the incentive of active investors to acquire firms in these industries. As a result, firms would start producing by polluting more.

[16] There is a trend in decarbonizing portfolio. See for instance: Portfolio Decarbonization Coalition (PDC)

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Tables / Figures

Figure 1: Importance of pollution among PE deals

Figure 1.A

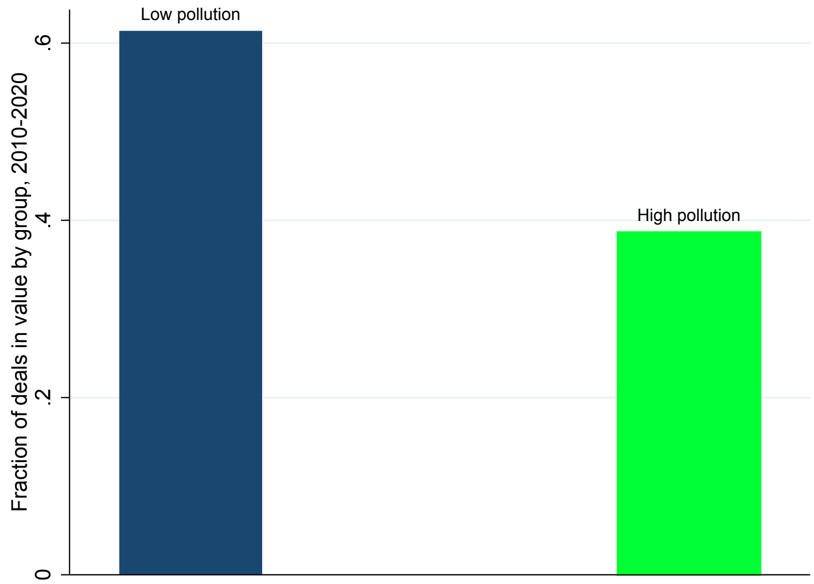
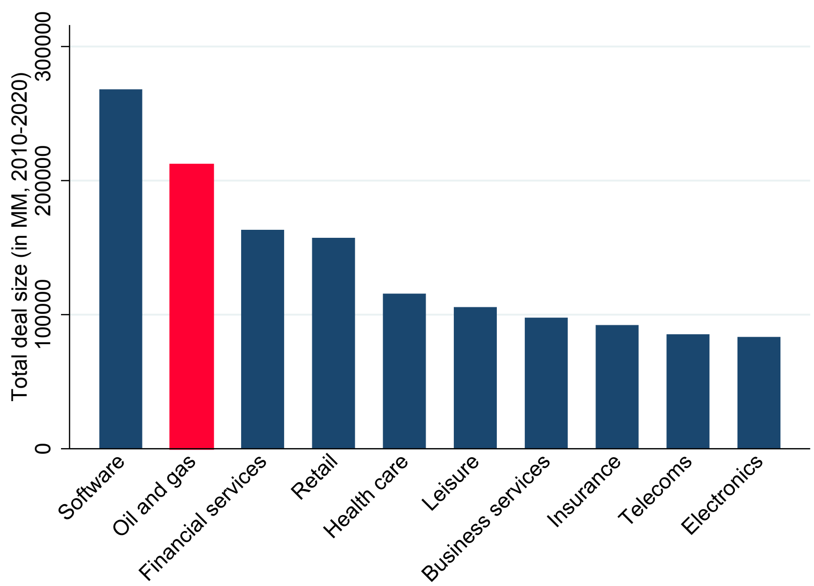


Figure 1.B



Note: Figure 1.A reports the fraction of PE investment in dollar value where a control right is transferred in industries that emit a significant amount of pollution. This includes natural resources, energy, transportation, infrastructure and manufacturing industries. Figure 1.B reports the cumulative amount of the deal size in million of dollars between 2010 and 2020 for the ten industries that have the highest amount of deals in dollar values. For both graphs, the investment types are: Add-on, Buyout, Growth Capital and PIPE.

Figure 2: Distribution Of Projects

Figure 2.A: all projects

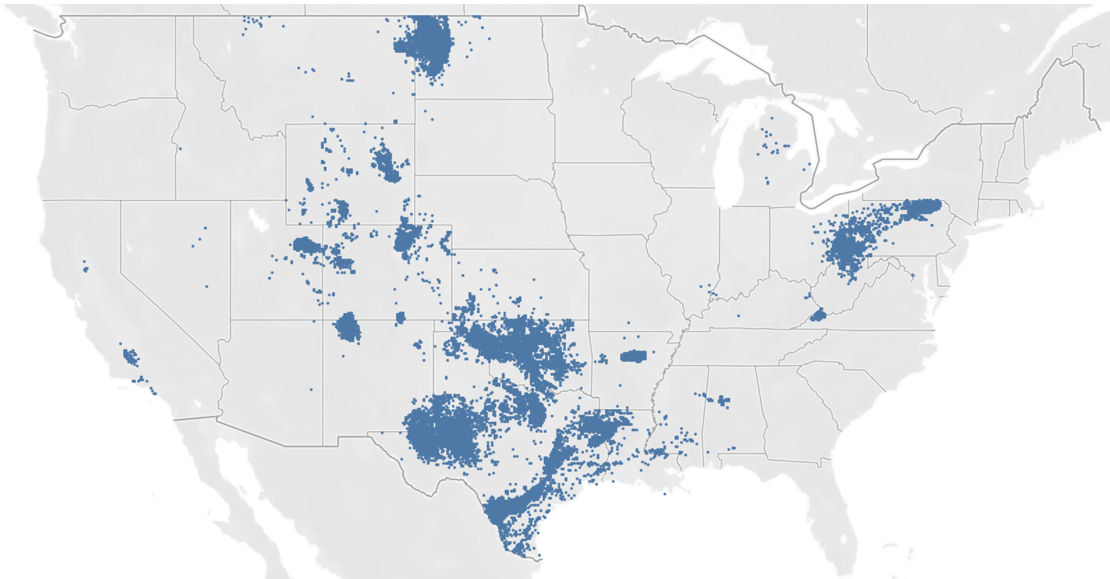
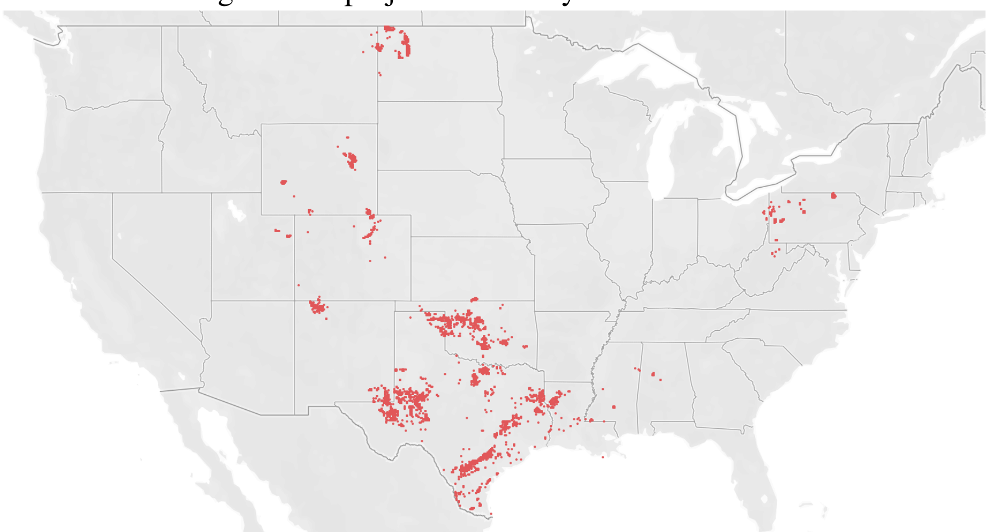
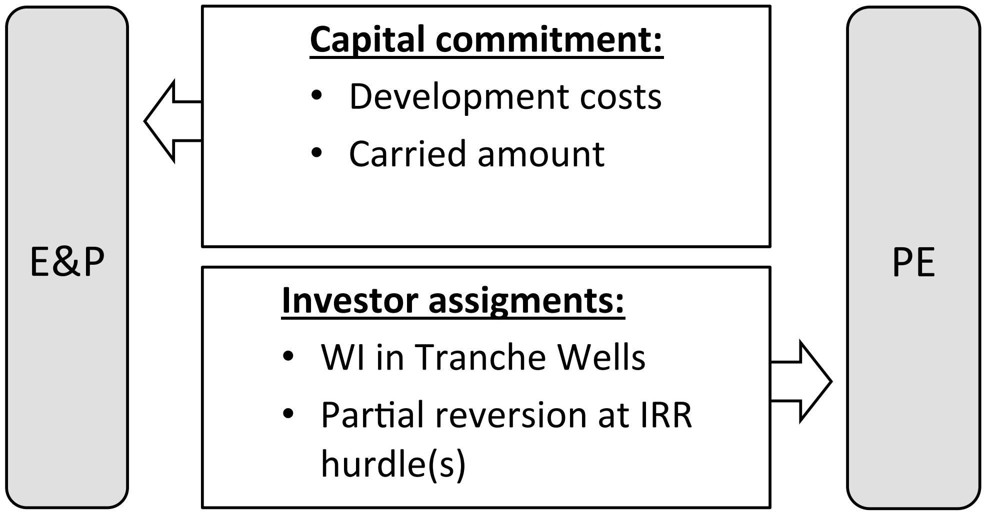


Figure 2.B: projects owned by PE-backed firms



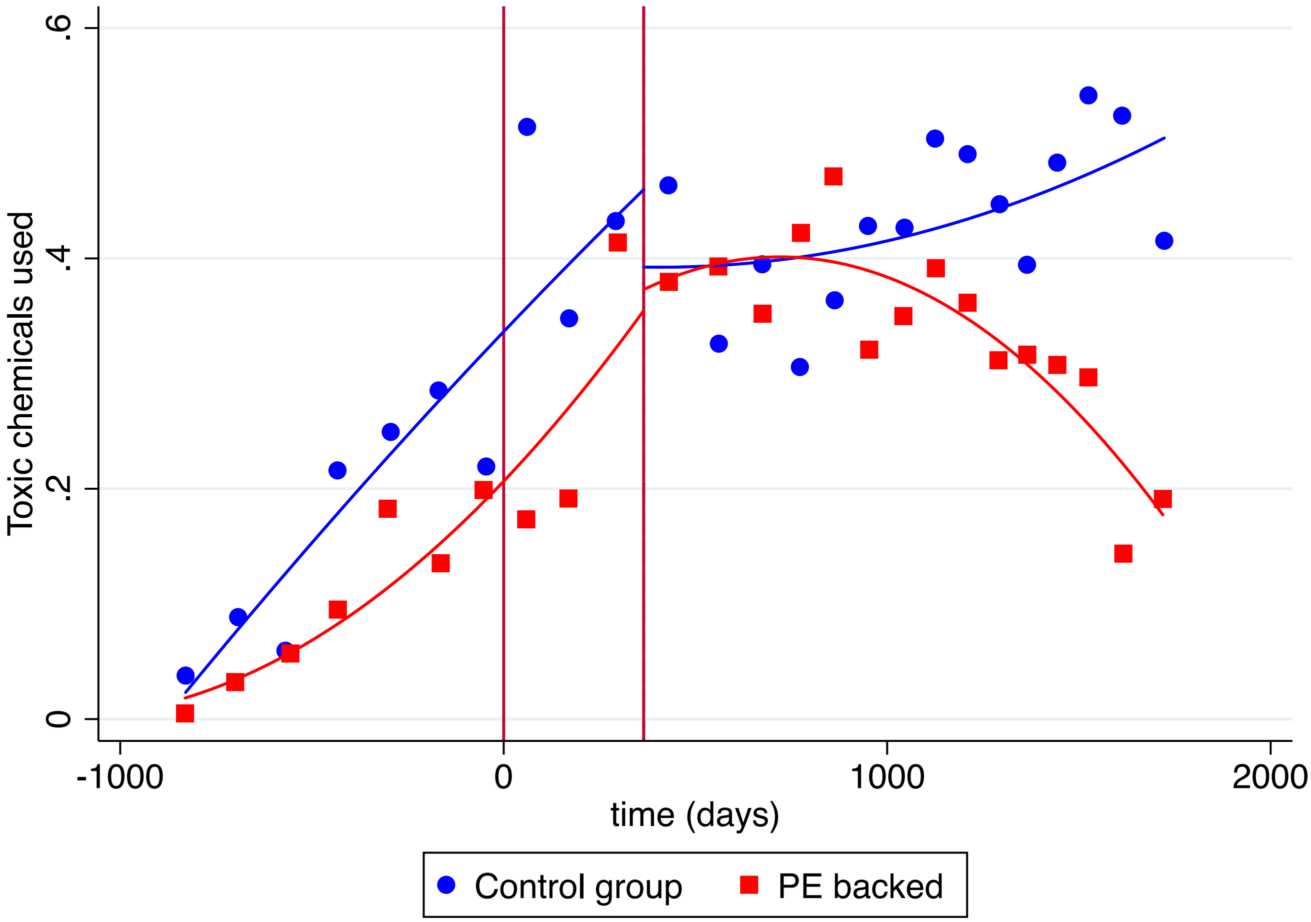
Note: These two figure show the location of the projects that I use in the statistical analysis. Sub-figure (a) shows all the projects, whereas sub-figure (b) only plots the projects that are owned by a PE-backed firm at some point in the sample.

Figure 3: Structure Of A DrillCo Deal



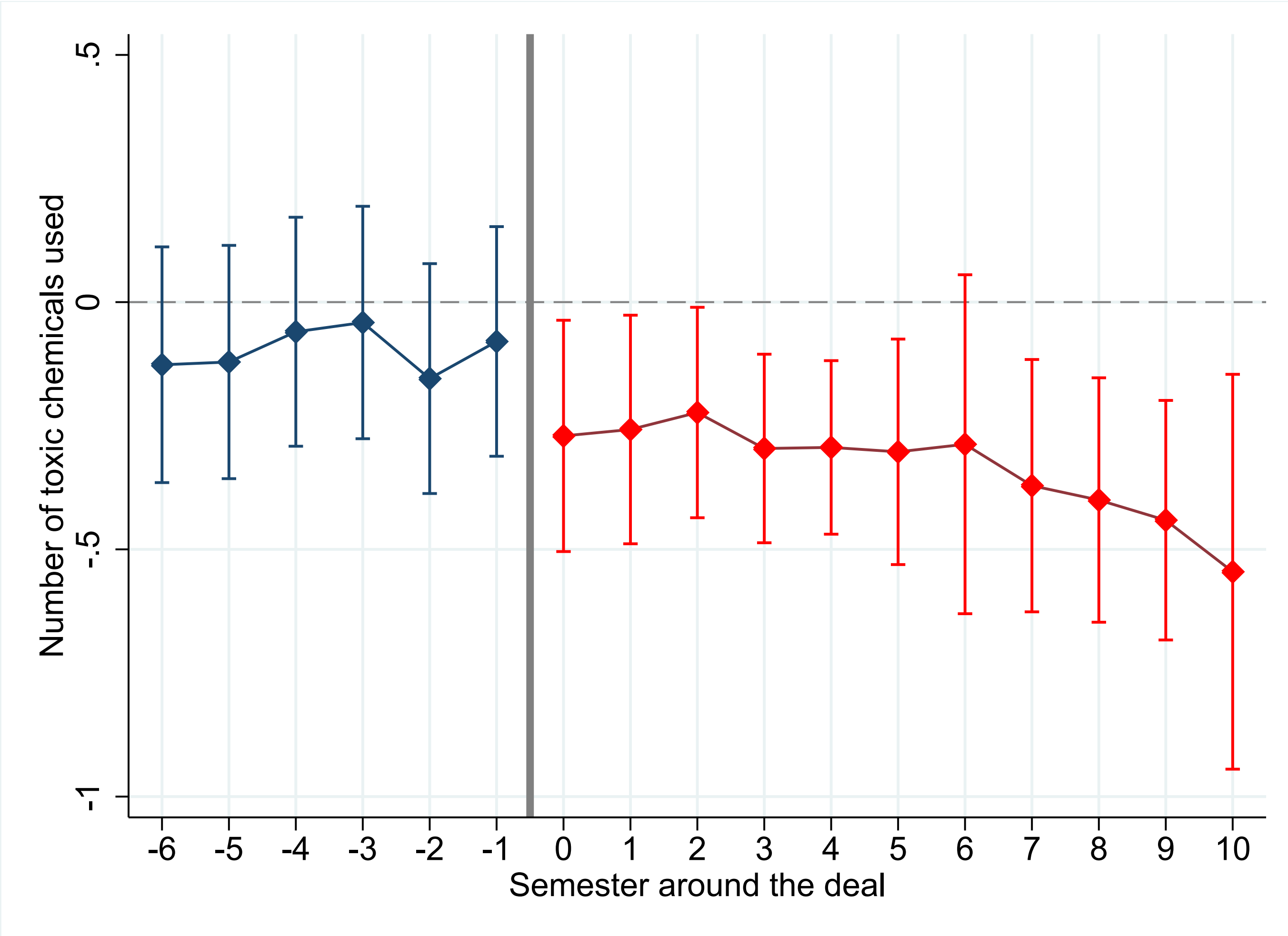
Note: This figure summarizes the structure of a DrillCo deal between a Private Equity (PE) firm and an exploration & production (E&P) company.

Figure 4: Raw Binscatter Of Pollution Around The PE Deal



Note: This figure reports the binscatter of the toxic chemicals used during the production process around the year of the PE deal. Each dot is the average of the number of toxic chemicals calculated on 5% of the sample that have the closest distance in days after or before the deal for both the treated and control group. Our treated group is the sample of projects made by firms that will be purchased by a PE, whereas our control group is the sample of projects made by firms that will not be purchased by a PE. The control group is constructed as follow: for each project among the treated group, we select with replacement the project in the control group that has been completed in the same basin and year, and has the closest size (horizontal length and vertical depth) and production (both oil and gas) using the mahalanobis metric. We restrict the analysis on the sample of firms that exist both before and after the deal for the treated group, although the graph remains similar if we include unbalanced firms. Notice here that we are performing the matching both before and after the deal, at the project level. The pattern observed is supporting the view that PE firms reduced pollution, and the effect is the strongest three years after the deal. This analysis should be interpreted in a non-causal way, as no fixed effect and controls are included.

Figure 5: Impact Of PE Buyout On The Number Of Toxic Chemicals

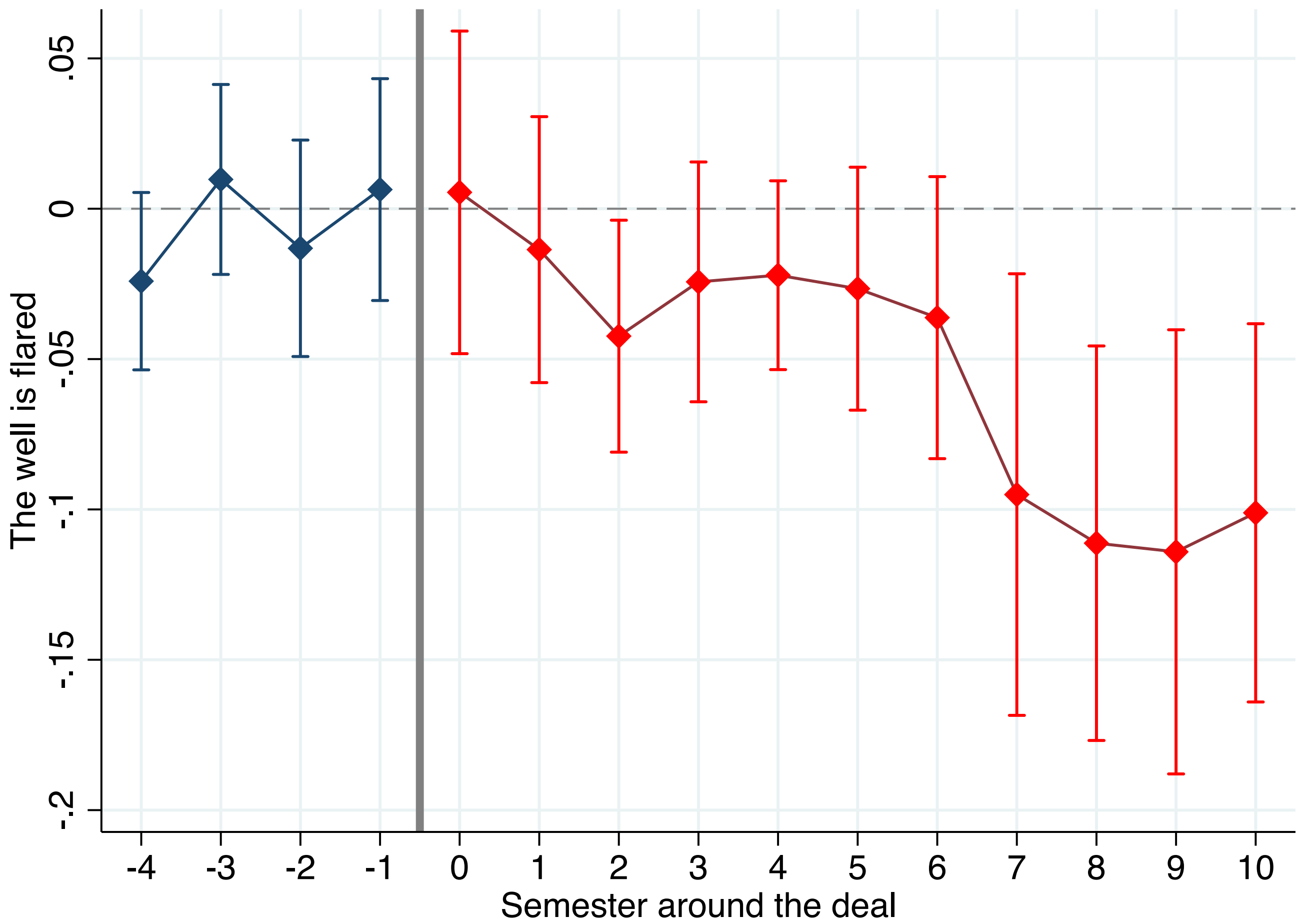


Note: This figure reports the dynamic difference-in-differences estimates around the PE buyout as well as its confidence interval estimated in the full sample. More specifically, the $(\gamma_\tau)_{\tau=-6,\ldots,9,10}$ of the following estimated equation are reported:

$$Y_{ijt} = \text{Firm}_i + \text{Location}_j \times \text{Year}_t + \sum_{\tau=-6}^{10} \gamma_\tau.(\tau \text{ semester(s) after the PE deal}) + controls_{it} + \varepsilon_{ijt}$$

Where Y_{ijt} is the total number of toxic chemicals used for a well and as defined in Table 1. Firm_i is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemical. Location_j is a geographical fixed effect, that regroups all wells that have the same first 2-digit longitude and latitude. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. This location fixed effect is interacted with a year Fixed effect (Year_t). $controls_{it}$ includes the production of oil and gas of the well, its vertical depth and horizontal length. Standard errors are clustered at the firm level and confidence intervals at the 5% level are reported.

Figure 6: Impact Of PE Buyout On Flaring

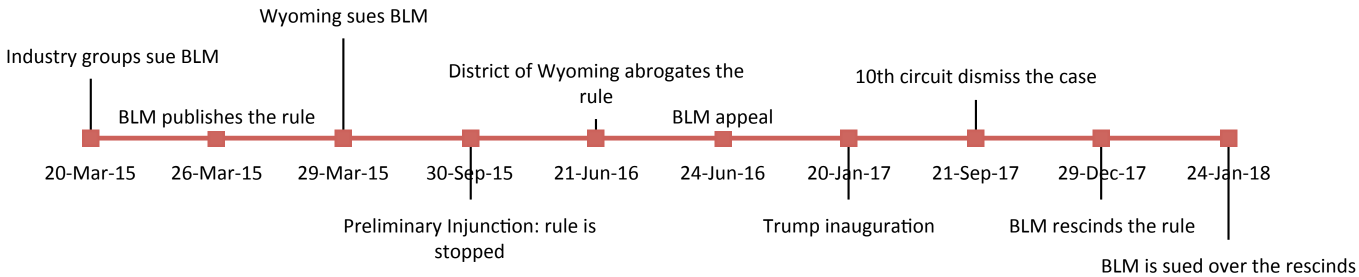


Note: The dependent variable takes one if the firm is flaring gas for the well i, 0 otherwise. I construct the depend variable using satellite data, available starting from 2012. I validate this data source by showing that the measure correctly captures the geographical (see figure A.1) and temporal (see figure A.2) distribution of well activities. I restrict the sample to wells that are not too close one from the other, although as we show in the online appendix, the results remain the same without this restriction. The dynamic difference-in-differences estimates around the PE buyout as well as its confidence interval are estimated using the full sample. The $(\gamma_\tau)_{\tau=-4,\ldots,9,10}$ of the following estimated equation are reported:

$$Y_{ijt} = \text{Firm}_i + \text{Location}_j \times \text{Year}_t + \sum_{\tau=-4}^{10} \gamma_\tau.(\tau \text{ semester(s) after the PE deal}) + controls_{it} + \varepsilon_{ijt}$$

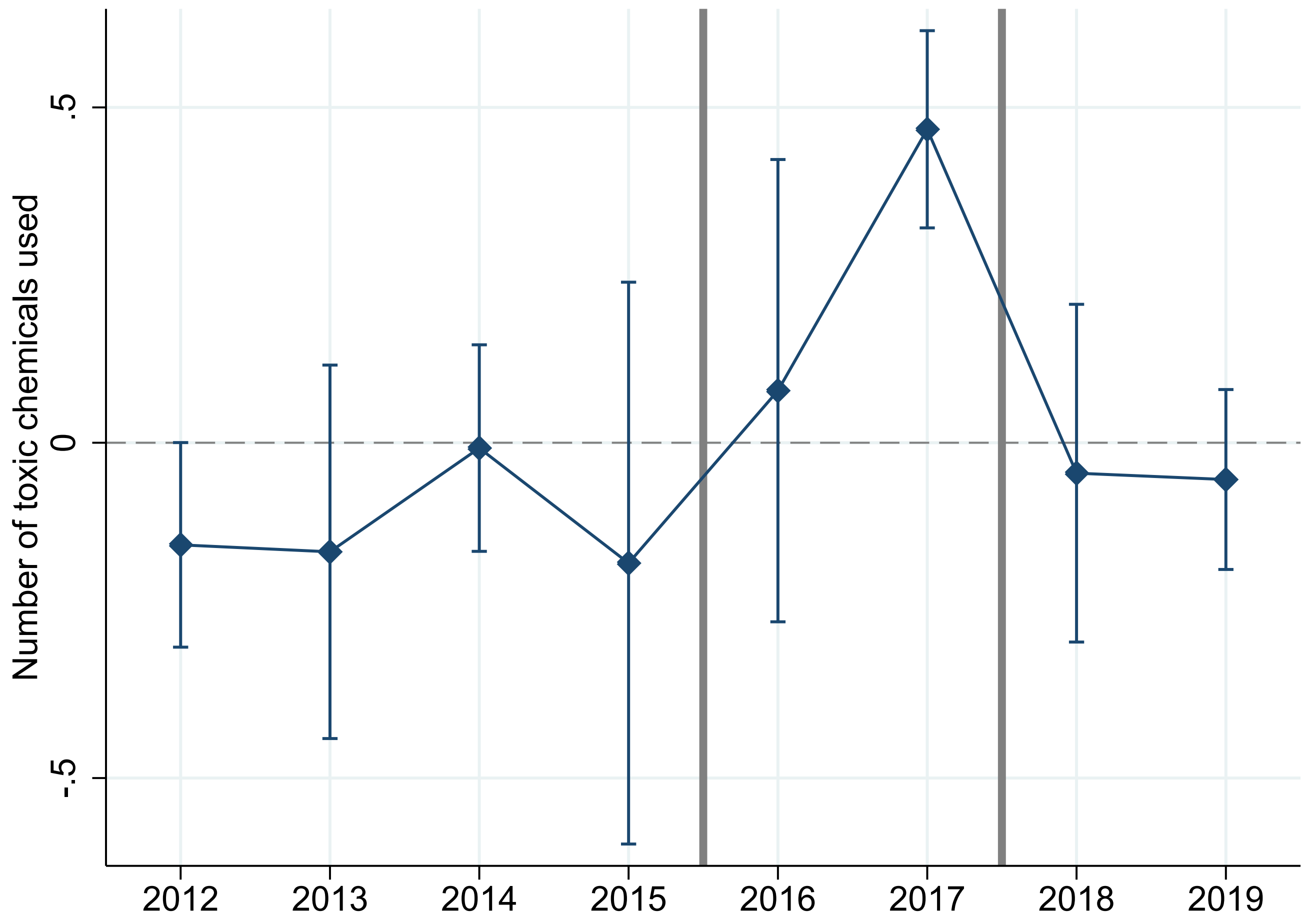
where Y_{ijt} is whether the company is flaring the well i. Firm_i is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to flare. Location_j is a geographical fixed effect, that regroups all wells that have the same first 2-digit longitude and latitude. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. $controls_{it}$ include the vertical depth and horizontal length of the well, but does not include the production variables, as they are mechanically correlated with the dependent variable. Standard errors are clustered at the firm level and confidence intervals at the 5% level are reported.

Figure 7: Timeline of the court proceedings concerning the fracking rule



Note: This figure reports the timeline of the main milestones concerning the court proceedings of BLM fracking rule.

Figure 8: Impact Of Decreased Litigation Risks

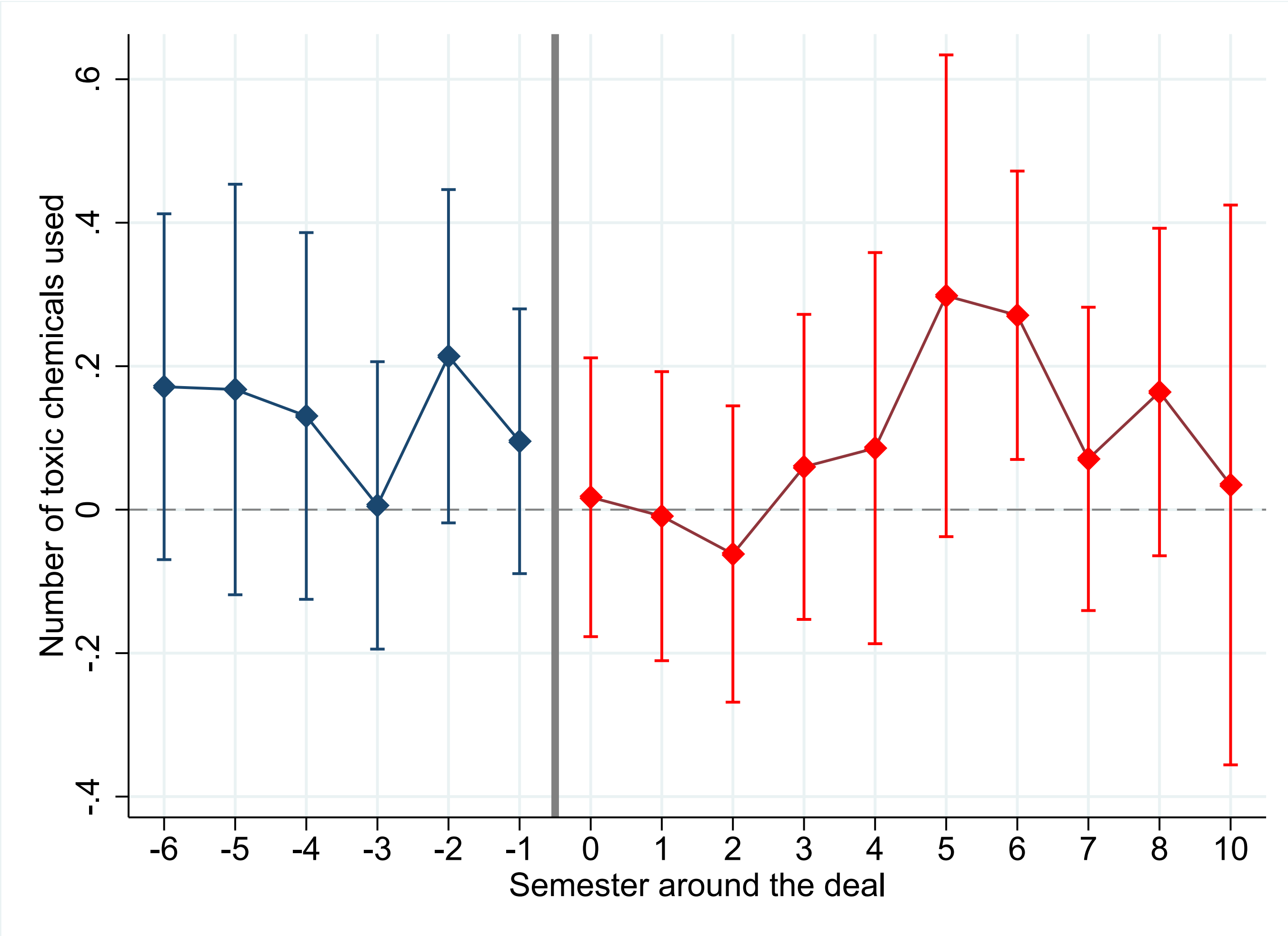


Note: This figure shows the dynamic triple difference-in-differences estimates on how PE-backed firms reacted to changes in BLM authority to regulate fracking in Federal lands and Native American reservations. More specifically, the $(\beta_\tau)_{\tau=2012,\ldots,2019}$ of the following estimated equation are reported:

$$Y_{ijt} = \text{Firm}_i \times \text{Year}_t + \text{Location}_j \times \text{Year}_t + \sum_{\tau=2012}^{2019} (\text{year=}\tau) \times (\text{BLM})_i \times (\gamma_\tau + \beta_\tau.\text{PE}_{it}) + controls_{it} + \varepsilon_{ijt}$$

Y_{ijt} is the total number of toxic chemicals used and as defined in Table 1. BLM_i is a dummy that takes one if the well is located in a Federal land or a Native American reservation, 0 otherwise. PE_{it} is a dummy taking one if the firm is owned by a PE firm. Firm_i is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemical. Location_j is a geographical fixed effect, that regroups all wells that have the same first 2-digit longitude and latitude. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. This location and firm fixed effect are both interacted with a year Fixed effect (Year_t). Standard errors are clustered at the firm level and confidence intervals at the 10% level are reported.
The two vertical lines separate the three regions that correspond to three different phases in this litigation. Specifically, 2012 to 2015 is the time period during which the BLM was writing the fracking rule. 2016 to 2017 include the time when the preliminary injunction was granted, the rule stroke down by the district of Wyoming and when the rule was voided by BLM (July 25, 2017) following the Trump administration. Finally, the period between 2018 and 2019 correspond to the time during which the State of California Jan. 24, 2018 sued BLM for his decision to rescind the rule.

Figure 9: Role Of Financial Constraints: Impact Of PE DrillCo On Pollution

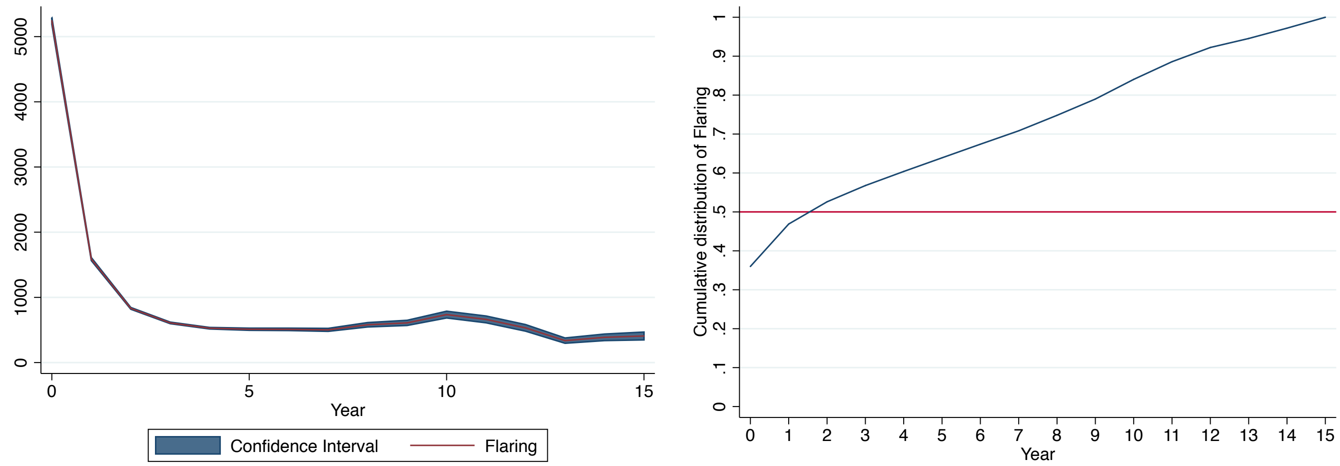


Note: This figure reports the dynamic difference-in-differences estimates around PE DrillCo deals as well as its confidence interval estimated in the full sample. DrillCo deals are PE funding without any transfer of control rights or changes in the firm's capital structure. The $(\gamma_\tau)_{\tau=-6,\dots,9,10}$ of the following estimated equation are reported:

$$Y_{ijt} = \text{Firm}_i + \text{Location}_j \times \text{Year}_t + \sum_{\tau=-6}^{10} \gamma_\tau.(\tau \text{ semester(s) after the PE deal}) + controls_{it} + \varepsilon_{ijt}$$

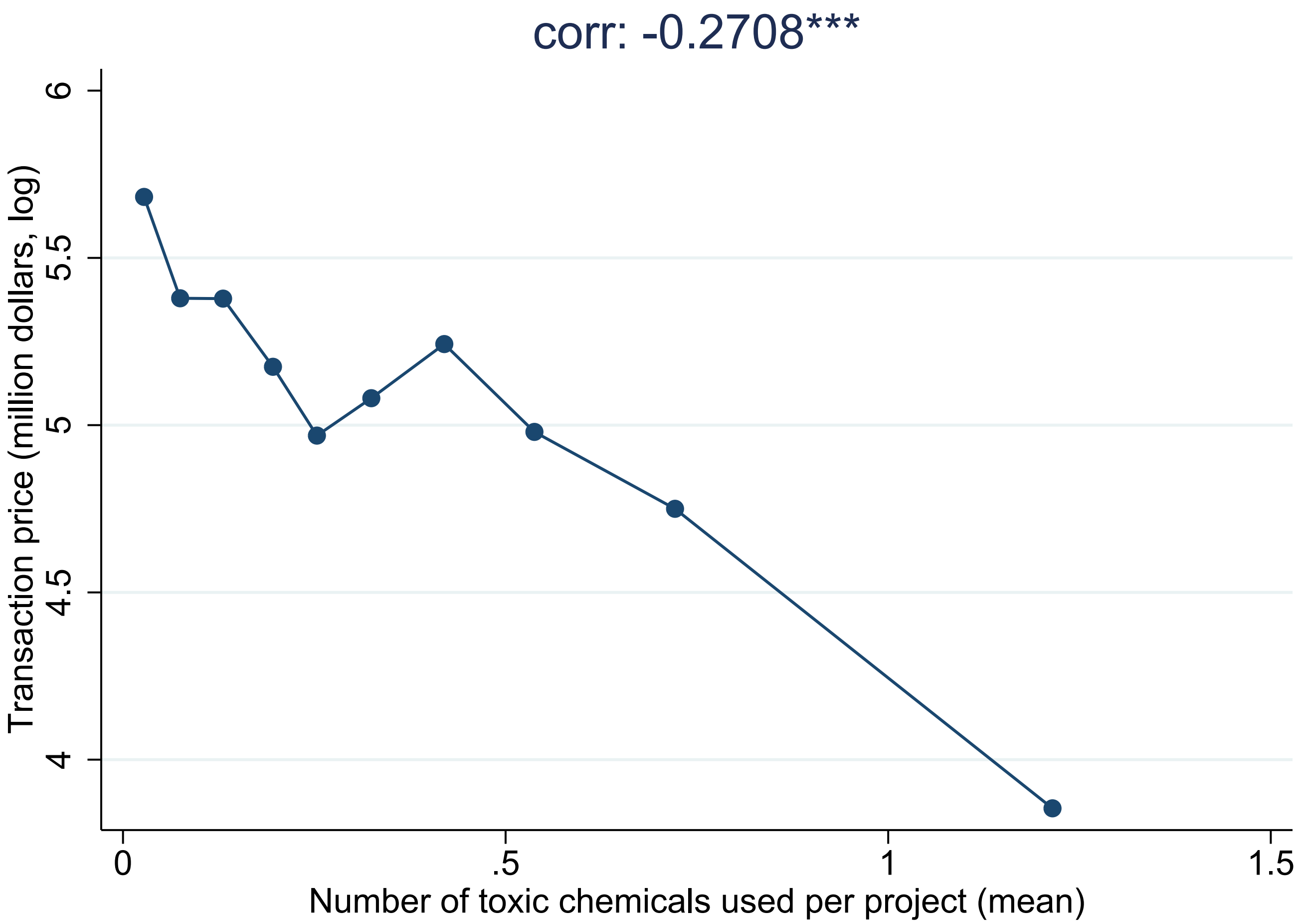
Where Y_{ijt} is the total number of toxic chemicals used for a well and as defined in Table 1. Firm_i is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemical. Location_j is a geographical fixed effect, that regroups all wells that have the same first 2-digit longitude and latitude. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. This location fixed effect is interacted with a year Fixed effect (Year_t). $controls_{it}$ includes the production of oil and gas of the well, its vertical depth and horizontal length. Standard errors are clustered at the firm level and confidence intervals at the 5% level are reported.

Figure 10: cash flows Of Flaring



Note: This graph reports the production curves of the gas flared for wells that are potentially not connected to a pipeline in North Dakota. The data come from the North Dakota Industrial Commission that requires operators to report the quantity of gas flared. The left Figure reports for each year after the well is completed, the total number of gas flared, in MCF (thousand cubic feet). The right figure represents the cumulative distribution of the amount of gas flared during the first 15 years. As can be seen, more than 50% of all the flared gas is done within the first 2 years after the well is completed. Whether the well is connected to a pipeline is confidential information. I make the assumption that wells flaring a large amount of gas are more likely not to be connected to a pipeline. Therefore, I first compute the total amount of gas flared during the well first 15 years and then I keep the 25% with the highest amount of flaring. The distributions look similar if I use different ways of selecting the data, only the level of the curves changes.

Figure 11: Negative Premium Of Pollution In Transactions Of Real Assets



Note: This figure reports the raw correlation between the price at which assets (acreage, properties or firms) are sold (in log) with the mean of the number of toxic chemicals that are used during the fracking phase. The raw correlation is equal to -0.27 and is statistically significant with a p-value below 1%.

Table 1: Definition And Source Of Toxic Chemicals

Chemical name	CAS number	Toxicity
2-butoxyethanol	111-76-2	cause hemolysis (destruction of red blood cells), spleen, liver, and bone marrow.
Xylene	1330-20-7	human carcinogen, SDWA, CAA
Toluene	108-88-3	human carcinogen, SDWA, CAA
Ethylbenzene	100-41-4	human carcinogen, SDWA, CAA
Benzene	71-43-2	human carcinogen, SDWA, CAA
Bis(2-ethylhexyl) phthalate	117-81-7	human carcinogen, SDWA, CAA
2-Propenamide	79-06-1	human carcinogen, SDWA, CAA
Copper	7440-50-8	human carcinogen, SDWA, CAA
Lead	7439-92-1	human carcinogen, SDWA, CAA

Note: The Table reports the chemicals used as our main dependent variable. They have in common that they are both highly toxic and salient as they have been reported in environmental reports as well as reports from the United States House of Representatives Committee on Energy and Commerce (for instance, April 2011). Most of them are regulated at the federal level, but the hydraulic fracturing benefits from several exemptions: this industry is not subject to the Safe Drinking Water Act (SDWA) and to several permitting and pollution control requirements from the Clean Air Act (CAA). Human carcinogens are substances that promote the formation of cancers.

Table 2: Descriptive Statistics

Panel A: Descriptive statistics, full sample (project level)

	Mean	S.D.	Min	Max
Number of toxic chemicals	.282	.546	0	4
Flaring	.216	.411	0	1
Productivity	8.043	32.632	0	2208
Production per fracturation	48.092	75.930	0	2340.63
Density population	107.571	616.922	0	6211.5
Density housing	47.1048	258.970	0	2479.6
Vertical depth	8984.05	2463.7	628	36386.56
horizontal depth	6552.907	2503.967	0	19982.37
First 6 months gas	256476.3	376568.3	0	8030048
First 6 months oil	45543.9	45877.21	0	608979

Panel B: Descriptive statistics, full sample (Firm level)

	mean	S.D.	min	max
Projects	97.49	490.65	1	7765
Basin	1.70	1.82	1	23
Coarser location	10.68	36.83	1	603
Location	2.94	5.42	1	85
State	1.372	1.1740	1	18

Note: These tables report the baseline descriptive statistics. Panel A reports information for the full sample at the project level and Panel B when data at the firm level are used.

Table 3: Comparison treated and control group: PE ownership

Panel A: Firm level

Variables	Group treated	Control group	Diff	S.D.
Projects	101.00	98.26	2.740	70.204
Basin	1.23	1.71	-0.397*	0.219
Coarser location	12.52	10.58	2.092	5.827
Location	2.94	2.91	0.031	1.014
State	0.98	1.38	-0.375*	0.203

Panel B: Project level

	Treated	Control	Diff.	S.D	Adj Diff	Adj S.D.
Nb toxic chemicals	0.18	0.29	-0.109	0.091	-0.086*	0.050
Flaring	0.14	0.15	-0.009	0.015	-0.007	0.017
Completion time	12.28	6.15	6.127***	2.179	6.649***	2.307
Prod. per Frac.	30.06	58.64	-28.577***	5.550	-1.145	1.500
Population	56.16	146.32	-90.158***	25.584	6.343	6.905
Housing	25.12	63.29	-38.174***	10.729	2.393	3.034
True Vertical Depth	9284.62	8472.03	812.586***	270.587	-92.787	80.136
Horizontal Length	5840.44	6606.14	-765.703***	192.083	-57.728	67.369
First 6 Gas	127451.91	231403.38	-103951.476***	24957.240	-2383.608	6038.700
First 6 Oil	44577.78	29711.73	14866.054**	6836.856	11747***	3986.702

Note: These tables report descriptive statistics. Panel A depicts the difference in characteristics when there is no PE ownership for both the control and treated group. Panel B reports the difference in characteristics at the firm level when there is no PE ownership for both the control and treated group. Adj diff and adj p are after the inclusion of the following FE, that are used in the regressions: (1) geographical groups based on the first two digits of the latitude and longitude interacted with a year FE. Standard errors are clustered at the basin-year level. S.D. stands for the standard deviation of the difference.

Table 4: Comparison Treated And Control Group: DrillCo Transactions

Panel A: Firm level

Variables	Group treated	Control group	Diff.	S.D.
Projects	387.89	89.03	298.914	197.390
Basin	2.18	1.67	0.504	0.615
Coarser location	27.75	10.17	17.576*	9.064
Location	5.29	2.85	2.438	1.706
State	1.57	1.36	0.214	0.413

Panel B: Project level

Variables	Group treated	Control group	Diff.	S.D.	Adj. Diff.	Adj. S.D.
Nb toxic chemicals	0.31	0.28	0.027	0.123	0.071	0.053
Flaring	0.1	0.15	-0.048	0.031	-0.022	0.034
Completion time	4.54	6.46	-1.92	1.513	0.582	0.401
Prod. per Frac.	43.08	59.22	-16.139	11.509	-2.441	2.244
Population	136.82	142.2	-5.375	91.913	-0.815	3.794
Housing	59.99	61.49	-1.507	38.614	-0.618	1.811
True Vertical Depth	8650.31	8487.59	162.719	427.494	20.226	60.098
Horizontal Length	6637.25	6543.04	94.209	554.741	173.417**	86.767
First 6 Gas	168061.98	233148.38	-65086.401*	35680.1	10744.812*	5901.011
First 6 Oil	25676.5	30436.48	-4759.975	8054.986	2627.599	2269.102

Note: These tables report descriptive statistics. Panel A depicts the difference in characteristics before a DrillCo is signed for both the control and treated group. Panel B reports the difference in characteristics at the firm level when there is no DrillCo signed for both the control and treated group. Adj diff and adj p are after the inclusion of the following FE, that are used in the regressions: (1) geographical groups based on the first two digits of the latitude and longitude interacted with a year FE. Standard errors are clustered at the basin-year level. S.D. stands for the standard deviation of the difference.

Table 5: Comparison Treated And Control Group: Native American reservations / Federal Lands And The Others

Variables	Group treated	Control group	Diff.	S.D.	Adj. Diff.	Adj. S.D.
Nb toxic chemicals	0.31	0.21	0.105**	0.05	0.017	0.029
Flaring	0.17	0.12	0.051*	0.029	0.013	0.009
Completion time	4.38	4.19	0.189	0.811	1.067*	0.547
Prod. per Frac.	44.2	57.04	-12.842*	7.637	-1.289*	0.762
Population	135.41	137.34	-1.929	48.067	-7.175*	4.189
Housing	54.83	60.28	-5.457	18.154	-3.389*	2.023
True Vertical Depth	8803.85	8384.6	419.254	364.981	51.574	41.177
Horizontal Length	6559.74	6010.92	548.824*	327.777	119.689	101.757
First 6 Gas	129676.43	189215.88	-59539.453**	24341.688	-3448.482	2236.68
First 6 Oil	20226.34	22241.5	-2015.155	3715.142	-43.474	765.643

Note: These tables report descriptive statistics. This table depicts the differences in characteristics between projects in federal lands and Native American reservations before the preliminary injunction of September 2015. Adj diff and adj p are after the inclusion of the following FE, that are used in the regressions: (1) geographical groups based on the first two digits of the latitude and longitude interacted with a year FE. Standard errors are clustered at the basin-year level. S.D. stands for the standard deviation of the difference.

Table 6: Impact Of PE On Pollution: Baseline Results

Panel A: Toxic chemicals

	Dependent variable: Number of toxic chemicals					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3) NNM	(4)	(5)	(6) NNM
Post deal	-0.198***	-0.198***	-0.209***	-0.038	-0.038	-0.022
	(0.054)	(0.054)	(0.036)	(0.046)	(0.046)	(0.048)
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Location × Year FE	X	X		X	X	
Basin × Year FE			X			X
Adjusted R^2	0.56	0.56	0.35	0.55	0.55	0.45
Observations	135554	135554	21433	135738	135738	28581

Panel B: Flaring

	Dependent variable: Whether the well is flared					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3) NNM	(4)	(5)	(6) NNM
Post deal	-0.044**	-0.045**	-0.028**	0.039***	0.040***	0.038***
	(0.019)	(0.019)	(0.013)	(0.010)	(0.011)	(0.010)
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Location × Year FE	X	X		X	X	
Basin × Year FE			X			X
Adjusted R^2	0.37	0.37	0.21	0.37	0.37	0.26
Observations	96787	96787	14252	96787	96787	21324

Note: Columns (1), (2) and (3) report the impact of PE ownership on pollution and columns (4), (5) and (6) study the impact of PE financing through DrillCo contracts on pollution. Column (1) and (4) estimate the relationship without controls, that are added in column (2) and (5). The coefficients remain stable when the controls are added. Column (3) and (6) contain the results when the relationship is estimated on the matched sample using a nearest neighbor matching (NNM) approach, both before and after the deal at the project level. The matched sample is constructed as follow: for each project that belongs to a firm that is acquired by a PE, we matched within the same geographical area (basin) and year, the project that has the closest size (horizontal length and vertical depth) and production (6 first months production of oil and gas). For Panel A, the dependent variable is the number of toxic chemicals used in the production process. Panel B reports the results where the dependent variable is a dummy that takes one if the project has flared gas. Standard errors are clustered at the firm level.

Table 7: Dynamic Effect

Panel A: Strength of the effect through time (PE ownership and control)

	Dependent variable: Number of toxic chemicals					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3) NNM	(4)	(5)	(6) NNM
Post deal × year(s) since deal	-0.069***	-0.069***	-0.086***	0.011	0.011	0.002
	(0.022)	(0.021)	(0.015)	(0.017)	(0.017)	(0.023)
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Basin × Year FE			X			X
Location × Year FE	X	X		X	X	
Adjusted R^2	0.56	0.56	0.36	0.55	0.55	0.45
Observations	135554	135554	21433	135554	135554	28581

Panel B: Strength of the effect through time (PE financing)

	Dependent variable: Number of toxic chemicals					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3) NNM	(4)	(5)	(6) NNM
Post deal × year(s) since deal	-0.020***	-0.020***	-0.009**	0.026**	0.026**	0.033***
	(0.007)	(0.007)	(0.004)	(0.012)	(0.012)	(0.012)
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Basin × Year FE			X			X
Location × Year FE	X	X		X	X	
Adjusted R^2	0.37	0.37	0.21	0.37	0.37	0.27
Observations	96787	96787	14252	96787	96787	21324

Note: This table replicates the baseline regression but interacts the variable "post deal" with the number of year(s) since the deal is signed. Columns (1), (2) and (3) report the impact of PE ownership on pollution and columns (4), (5) and (6) study the impact of PE financing through DrillCo contracts on pollution. Column (1) and (4) estimate the relationship without controls, that are added in column (2) and (5). The coefficients remain stable when the controls are added. Column (3) and (6) contain the results when the relationship is estimated on the matched sample using a nearest neighbor matching (NNM) approach, both before and after the deal at the project level. The matched sample is constructed as follow: for each project that belongs to a firm that is acquired by a PE, we matched within the same geographical area (basin) and year, the project that has the closest size (horizontal length and vertical depth) and production (6 first months production of oil and gas). For Panel A, the dependent variable is the number of toxic chemicals used in the production process. Panel B reports the results where the dependent variable is a dummy that takes one if the project has flared gas. Standard errors are clustered at the firm level.

Table 8: BLM Natural Experiment

Panel A: triple difference-in-differences

	Dependent variable: Number of toxic chemicals			
	(1)	(2)	(3)	(4)
Federal or Indian well × Post deal × Post Injunction	0.383***	0.382***	0.308***	0.309***
	(0.090)	(0.091)	(0.084)	(0.084)
Post deal × Post Injunction	-0.016	-0.016	-0.005	-0.005
	(0.054)	(0.054)	(0.058)	(0.058)
Federal or Indian well × Post deal	-0.053	-0.052	-0.032	-0.033
	(0.055)	(0.055)	(0.061)	(0.061)
Federal or Indian well × Post Injunction	-0.015	-0.015	-0.045	-0.045
	(0.052)	(0.052)	(0.046)	(0.046)
Post deal	-0.191***	-0.191***	(.)	(.)
	(0.056)	(0.056)	(.)	(.)
Federal or Indian well	0.033	0.033	0.044*	0.044*
	(0.026)	(0.026)	(0.024)	(0.024)
Post Injunction	0.014	0.015	0.013	0.013
	(0.024)	(0.023)	(0.024)	(0.024)
Controls		X		X
Firm × Year FE			X	X
Firm FE	X	X		
Location × Year FE	X	X	X	X
Adjusted R^2	0.56	0.56	0.62	0.62
Observations	135738	135738	135257	135257

Panel B: Net effect

	Dependent variable: Number of toxic chemicals			
	(1)	(2)	(3)	(4)
Federal or Indian well × Post deal × Post Injunction	0.347***	0.346***	0.275***	0.275***
	(0.066)	(0.066)	(0.064)	(0.064)
Controls		X		X
Firm × Year FE			X	X
Firm FE	X	X		
Location × Year FE	X	X	X	X
Adjusted R^2	0.55	0.55	0.62	0.62
Observations	135738	135738	135257	135257

Note: Panel A reports a triple difference-in-differences that estimate the differential impact of the BLM litigation on pollution for Native American reservations and federal lands for firms that are owned by a PE firm. The variable "Post Injunction" takes the value one if the project starts between 30/09/2015 (day of the preliminary injunction) and 24/01/2018 (day when the State of California sued BLM over the rescission). The coefficient of particular interest is: Federal or Indian well × Post deal × Post Injunction and is negative, which shows that PE-backed firm increases pollution following a reduction in litigation and compliance risks. Panel B reports the net effect. For both panels, columns (1) and (2) contain a firm fixed effect, whereas columns (3) and (4) contain a firm-year fixed effect. Controls are added in column (2) and (4) and the coefficients of interest remain stable.

ONLINE APPENDIX

Quote And Citations From The Main PE Sponsors In The Oil And Gas Industry

“Well-managed sustainability strategies not only reduce pressure on our resources, they also yield operational cost savings, healthier and more productive work environments, and more valuable assets." "Saving water helps to preserve our environment as it is limited resource on earth and it will help to ensure a sustainable adequate water supply in future". **TPG Capital**.

“Protecting the environment of the communities in which we operate is critically important." **GSO Capital Partners**.

“We firmly believe that ESG issues can affect the risk-adjusted performance of our investment portfolios to varying degrees across asset classes over time". **GCP Capital Partners**.

“Contributed to national environmental standards formulation process through collaboration with the US Department of Energy to improve shale gas production best practices, disclosure and technology". **First Reserve Corporation**.

“We encourage and embrace the efficient use of natural resources and continuously look for and expect the best environmental solutions for our portfolio companies’ operations. We believe that economic considerations in isolation do not provide sufficient guidance for environmentally conscious decision-making that balances the interests of individuals, communities and future generations. We seek to fully comply and/or exceed compliance with applicable environmental regulatory requirements." **EnCap Investments**.

“We recognize the importance of climate change, biodiversity, and human rights, and believe negative impacts on project-affected ecosystems, communities, and the climate should be avoided". **Denham Capital Management**.

“Seek to grow and improve the companies in which they invest for long-term sustainability and to benefit multiple stakeholders, including on environmental, social and governance issues". **Carlyle Group.**

“Protecting the environment of the communities in which we operate is critically important". **Blackstone Group**.

Figure A.1: Geographical Distribution Of Flaring Practices

This figure plots the geographical distribution of the practice of flaring as detected by the satellite measure. It matches the spatial distribution of oil and gas basins.

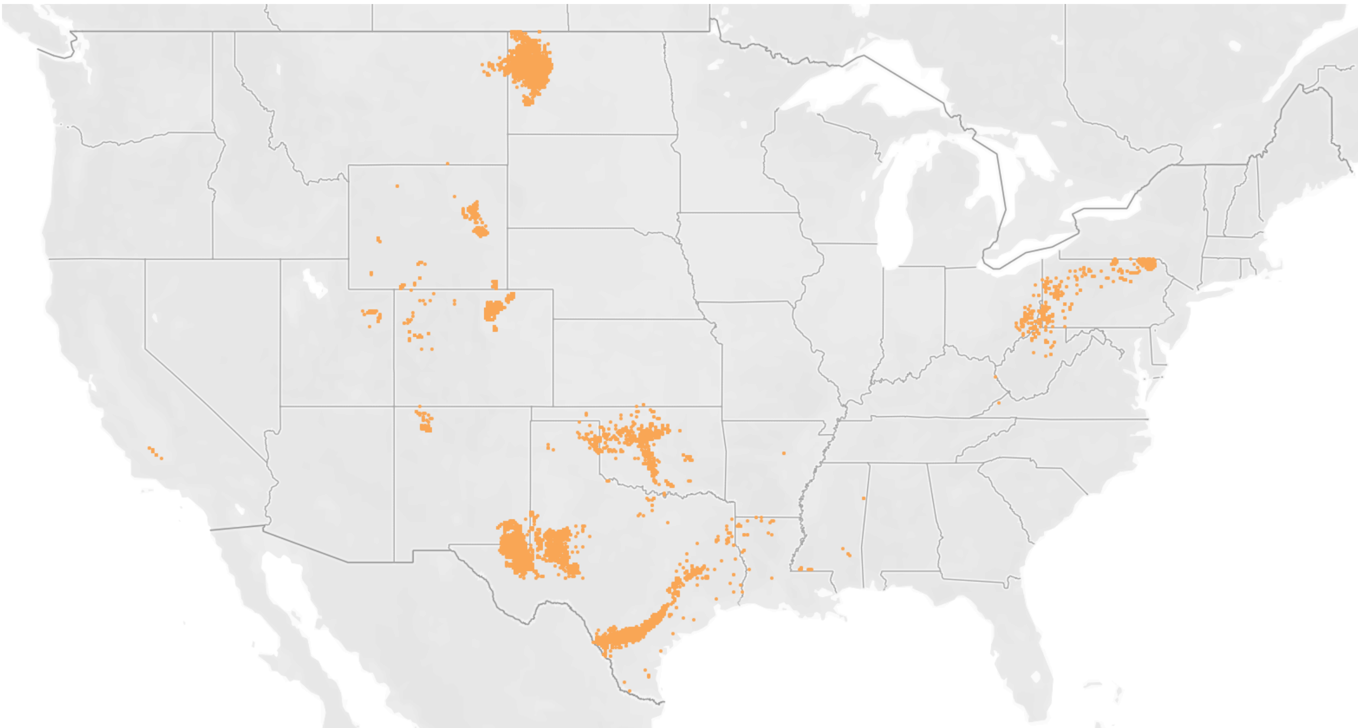


Figure A.2: Probability Of Observing Flaring Before And After The Well Completion

This figure plots the probability of observing the practice of flaring as detected by the satellite measure before and after the well completion. The pattern is consistent with the idea that the satellite measure is able to detect correctly the practice of flaring.

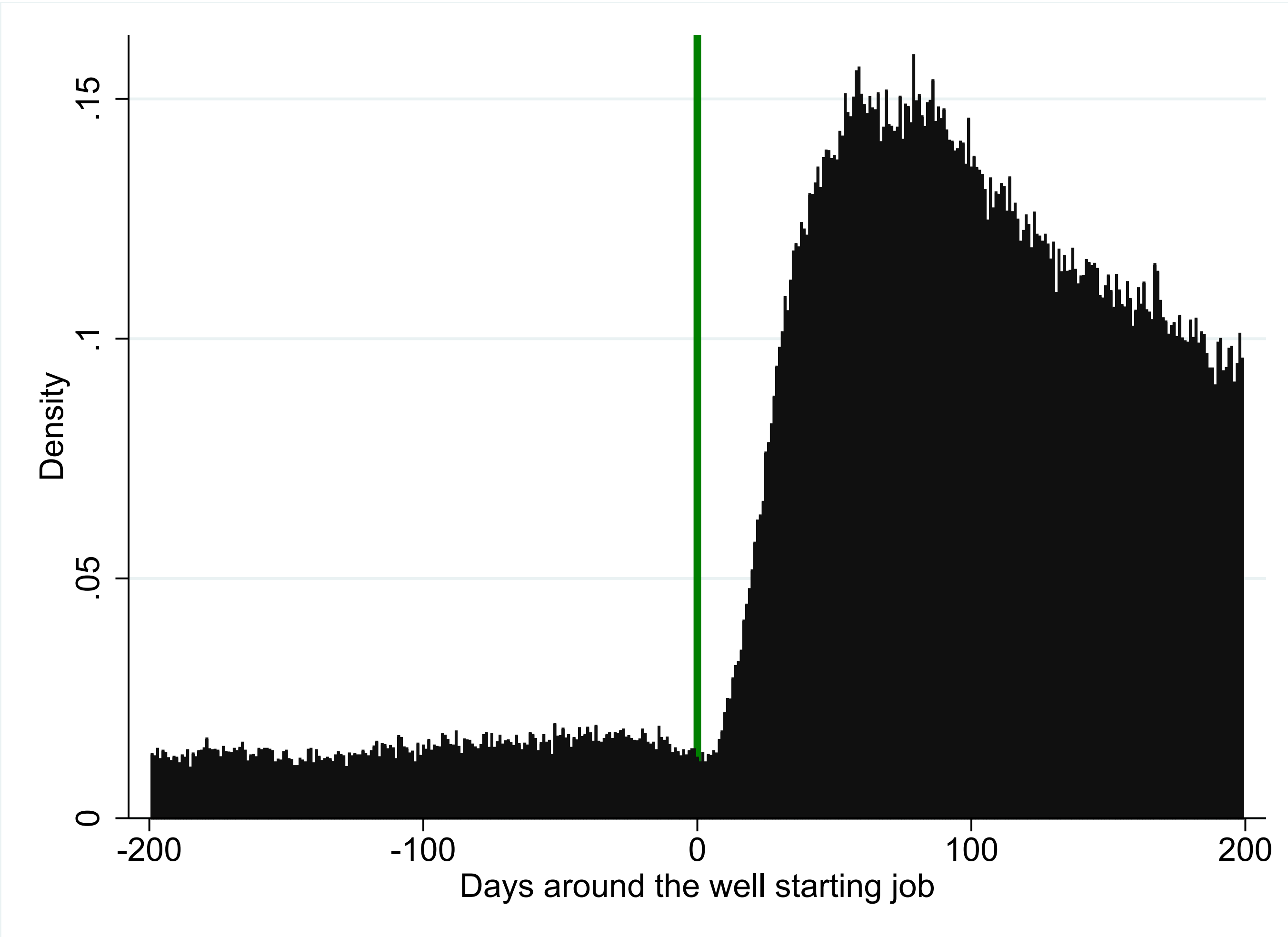
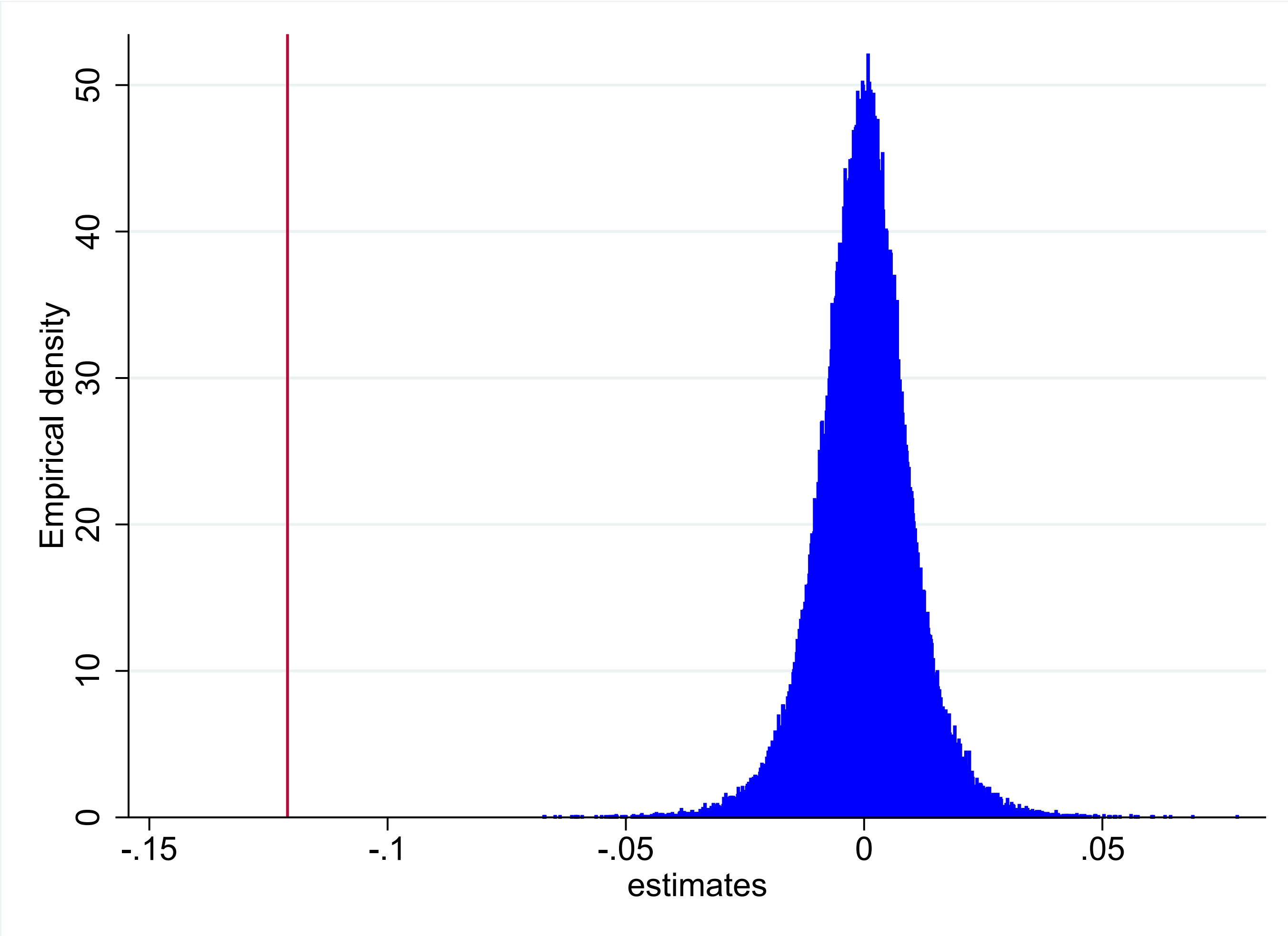


Figure A.3: Bootstrapped Placebo



Note: this graph plots the frequencies of the β estimated of the following equation:

$$Y_{ijt} = \text{Firm}_i + \text{Year}_t \times \text{Location}_j + \beta.(\text{Placebo post deal dummy})_{it} + controls_{ijt} + \varepsilon_{ijt} \tag{2.b}$$

for 200,000 different samples. For each sample, I simulate 106 randomly picked firms after dropping from the sample our 106 treated firms. For these 106 randomly picked firms, I simulate 106 post periods, where $(\text{Placebo post deal dummy})_{it}$ takes the value one. The fixed effects and the controls are the same than the ones in the previous samples. The red vertical line is at -0.121, which is the value of the beta when estimated on the real treated sample.

Figure A.4: High-frequency Geographical Fixed Effect: Geographical Example Using The Marcellus Formation

This map illustrates the coarser geographical fixed effect after zooming on the Marcellus formation.

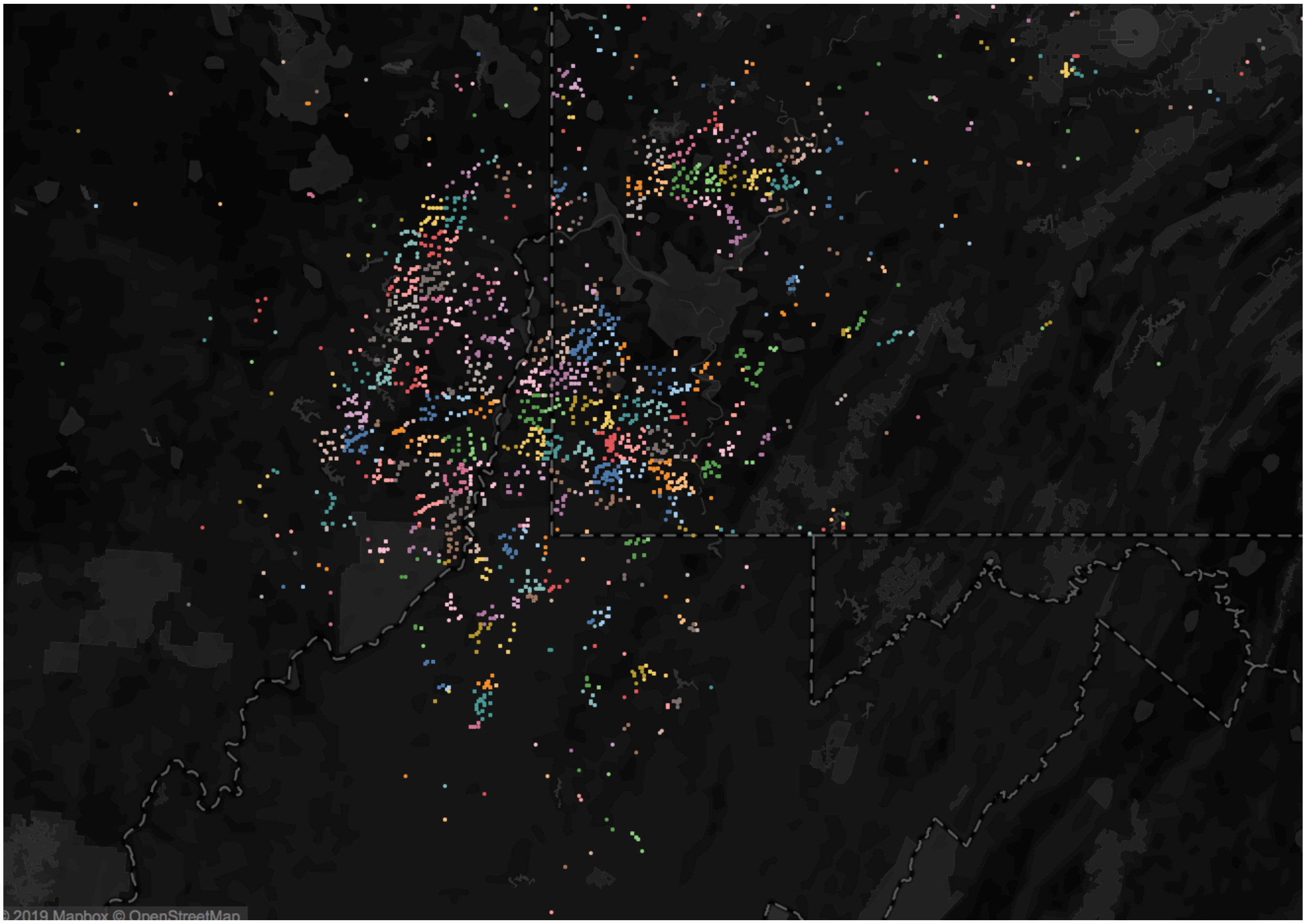


Figure A.5: Geographical Fixed Effect: Illustration Of The Longitude And Latitude Unit Square

This Table plots the 60 miles by 60 miles geographical fixed effect.

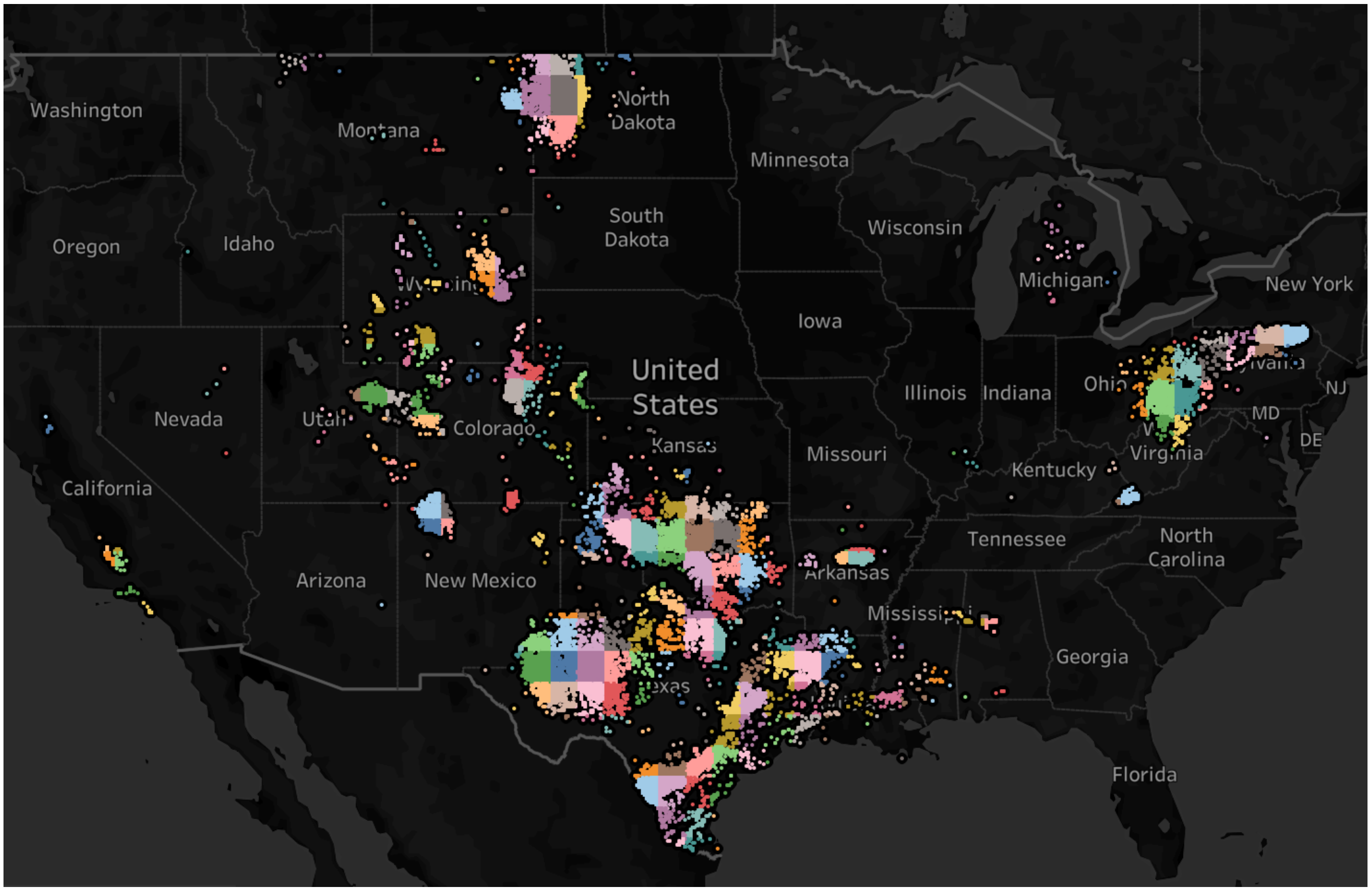
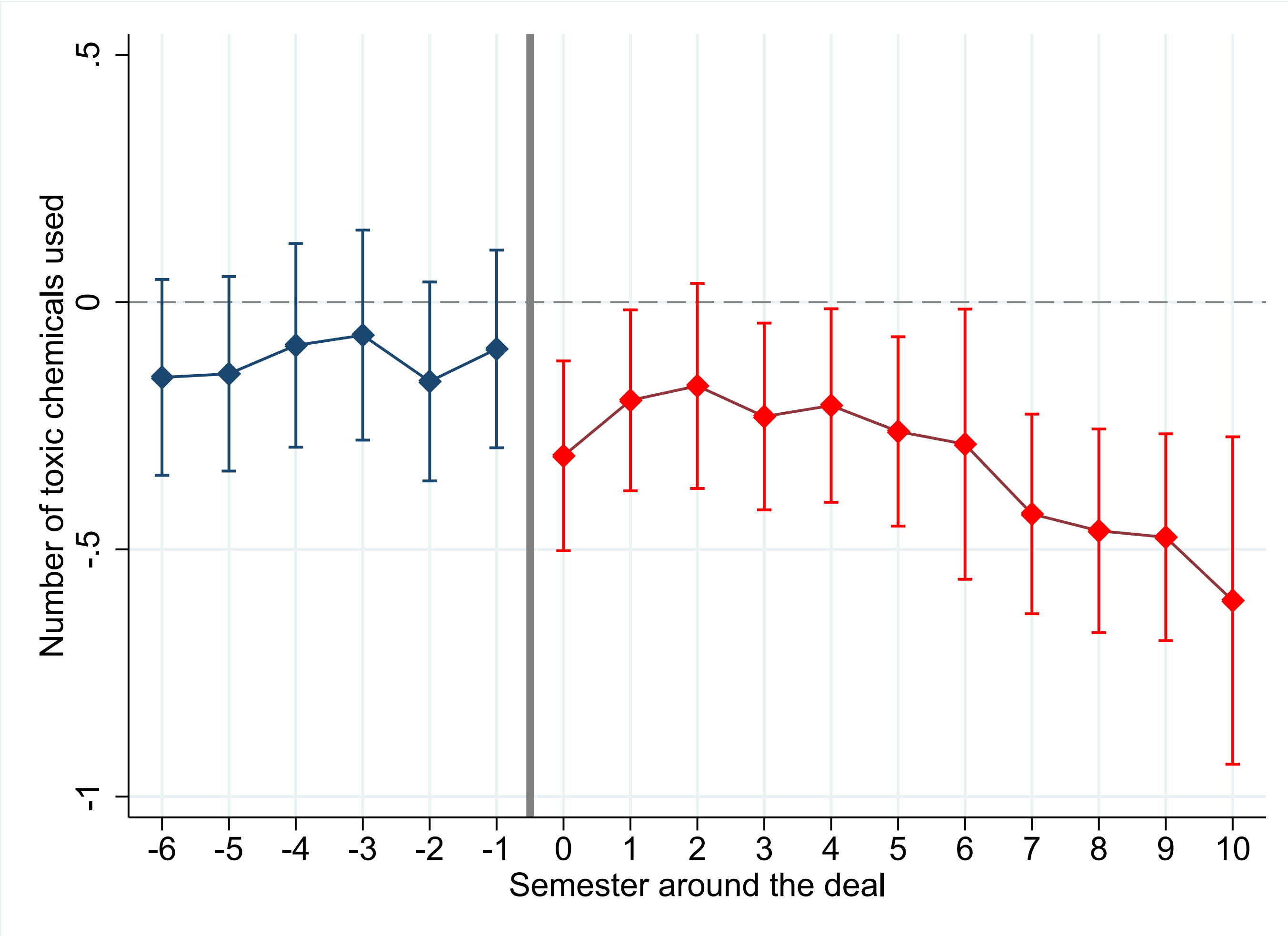


Figure A.6: Impact Of PE Buyout On The Number Of Toxic Chemicals: robustness test



Note: This figure reports the dynamic difference-in-differences estimates around the PE buyout as well as its confidence interval estimated in the full sample. More specifically, the $(\gamma_\tau)_{\tau=-6,...,9,10}$ of the following estimated equation are reported:

$$Y_{ikt} = ID_i + BY_{jt} + GEO\_coarse_k + \sum_{\tau=-6}^{10} \gamma_\tau.(\tau \text{ semester(s) after the PE deal}) + controls_{it} + \varepsilon_{ikjt}$$

where Y_{ijt} is the total number of toxic chemicals used for a well and as defined in Table 1. ID_i is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemical. BY_{tj} is a geographical-time fixed effect, that regroups within the same year, wells that are in the same basin, the same state as well as the same latitude and longitude unit (equivalent to 60 by 60 miles square). Figure A.5 maps the different regions that are used to construct the 60 by 60 miles square. Finally, GEO_coarse_k is a fixed effect that regroups wells within the same first two digits of the latitude and longitude -equivalent to a 7 miles to 4 miles square-. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. $controls_{it}$ includes the production of oil and gas of the well, its vertical depth and horizontal length. Standard errors are clustered at the firm level and confidence intervals at the 5% level are reported.

Figure A.7: Impact Of Decreased Litigation Risks

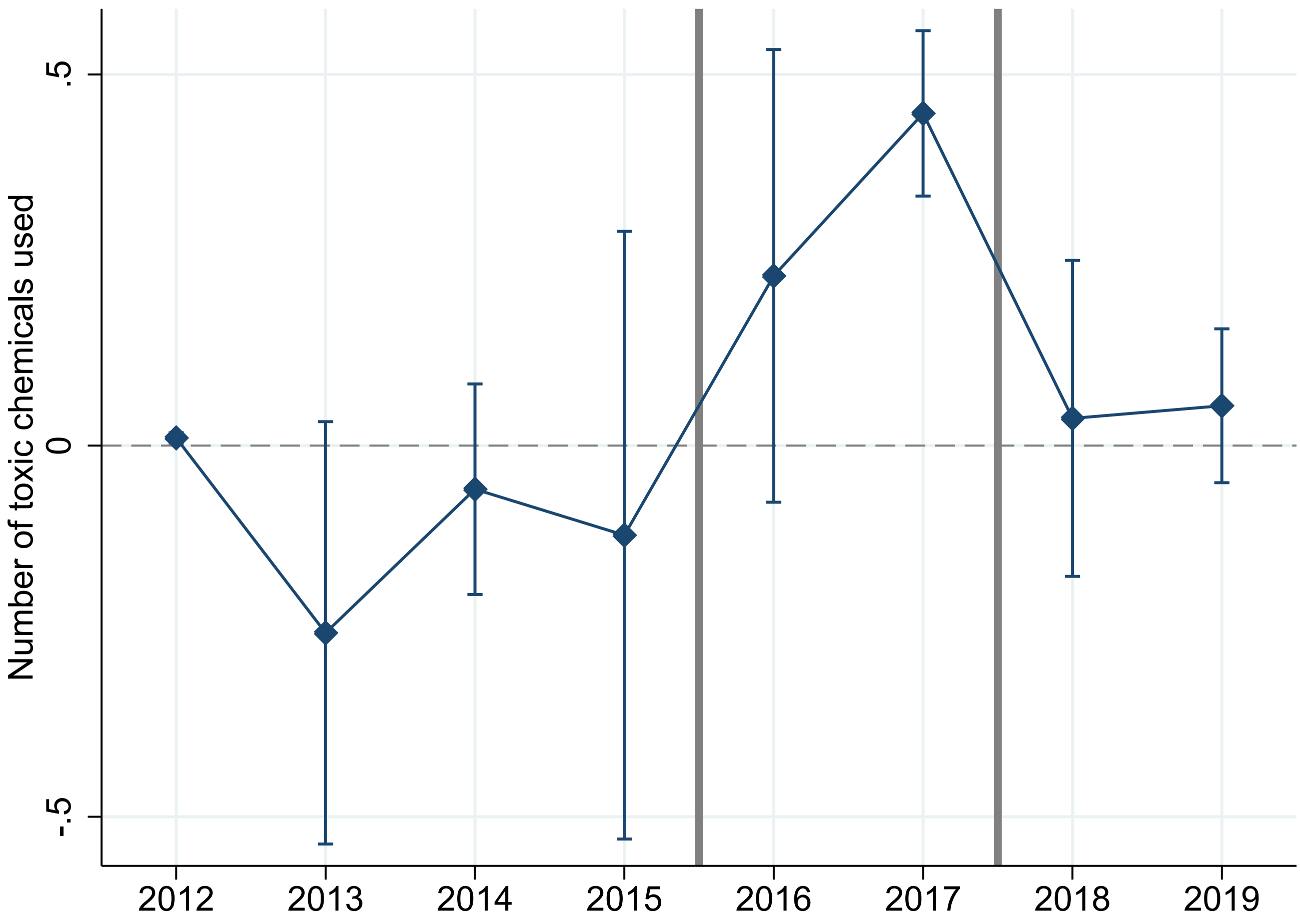
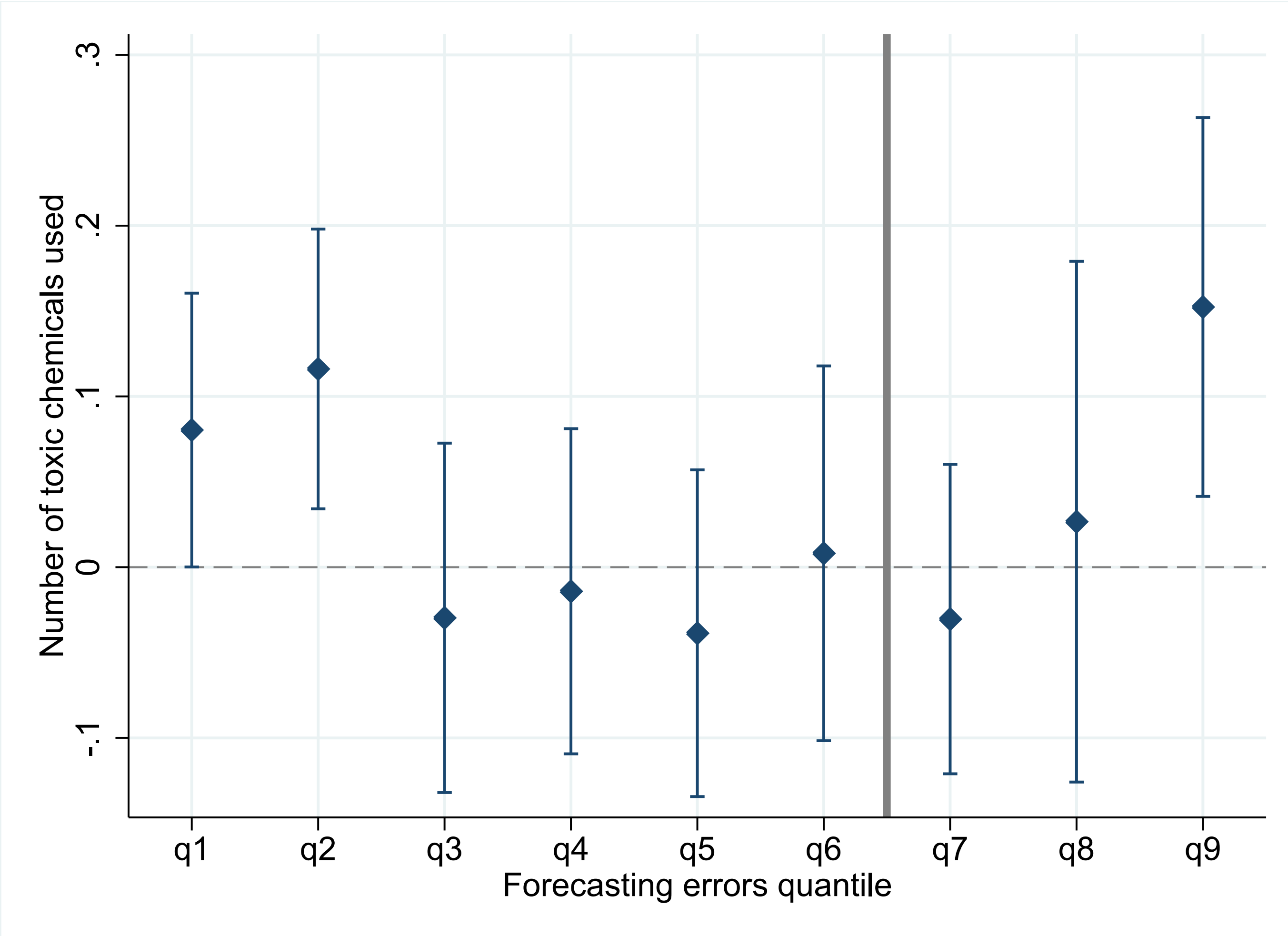


Figure A.8: Role Of EPS Targets On Toxic Chemicals



Note: This figure plots the estimates $(q_\tau)_{\tau=1,\ldots,9}$ of the following regression:

$$Y_{ijt} = \text{Firm}_i + \text{Location}_j \times \text{Year}_t + \sum_{\tau=1}^{9} q_\tau.(\tau \text{ decile of the forecast errors})_{it} + controls_{ijt} + \varepsilon_{ijt}$$

The variable $(\tau \text{ decile of the forecast errors})_{it}$ is constructed as follow. We first calculate the differences between the average one year forecast of earning per share (EPS) made by analysts and the realized one. This provides us a measure of how accurate the analysts forecast were. Then, we take the decile of the errors for each year-firm observations. $(\tau \text{ decile of the forecast errors})_{it}$ is a dummy that is equal to one if the project i made at time t belongs to a firm that has an error of EPS forecast that belongs to the quantile τ. The horizontal bar separates errors where analysts are wrong because they anticipate a higher EPS than the realized one (left side) from the cases where they anticipate a lower EPS than the realized one (right side).
The rest of the variables are the same as before. Namely, Y_{ijt} is the total number of toxic chemicals used for a well and as defined in Table 1. Firm$_i$ is an operator fixed effect, that captures any heterogeneity at the firm level that is constant through time and affects the decision to use toxic chemical. Location$_j$ is a geographical fixed effect, that regroups all wells that have the same first 2-digit longitude and latitude. To illustrate this grouping, Figure A.4 plots the wells with a same color if they have the same first two digits of latitude and longitude and if they are situated in one half of the Marcellus formation. This location fixed effect is interacted with a year Fixed effect (Year$_t$). $controls_{it}$ includes the production of oil and gas of the well, its vertical depth and horizontal length as well as the realized EPS. Standard errors are clustered at the firm level and confidence intervals at the 5% level are reported.

Table A.1: Reporting

2010	2011	2012	2013	2014	2015
Wyoming	Louisiana	Colorado	Alabama	Alaska	Kentucky
	Michigan	Idaho	Arkansas	California	North Carolina
	Montana	Indiana	Kansas	Illinois	
	Texas	New Mexico	Mississippi	Nevada	
		North Dakota	Nebraska	West Virginia	
		Ohio	Tennessee		
		Oklahoma	Utah		
		Pennsylvania			
		South Dakota			

Note: This Table shows the year when reporting to FracFocus became mandatory.

Table A.2: Results On Marginal Wells

Panel A: Marginal well within the firm

	Dependent variable: Number of toxic chemicals			
	(1)	(2)	(3)	(4)
Post deal	-0.183***	-0.174***	-0.268***	-0.162***
	(0.054)	(0.062)	(0.066)	(0.040)
Observations	134551	133301	130848	128572
Controls	X	X	X	X
Firm FE	X	X	X	X
Location × Year FE	X	X	X	X

Panel B: Marginal well within the basin

	Dependent variable: Number of toxic chemicals		
	(1)	(2)	(3)
Post deal	-0.198***	-0.219***	-0.297***
	(0.054)	(0.065)	(0.096)
Observations	134512	130566	128078
Controls	X	X	X
Firm FE	X	X	X
Location × Year FE	X	X	X

Note: This table replicates the baseline regressions after dropping projects that are in places that could create an endogeneity problem. Panel A drops project from PE-backed firms that are in their main region of activity. Specifically, I first calculate the variable C= $\frac{\text{Number of projects in basin j for firm i}}{\text{Total number of project of firm i}}$. If the ratio C is low, then it implies that this basin is a marginal location for the PE firm and is therefore less likely to be the main reason for which a PE bought the company in the first place. I take different threshold value for what "low" means. Equation (1) drops firms that drill in only one location (ratio=1). Equation (2) estimates the baseline relationship on locations that account for less than 0.77 of the total firm project (.77 is the 75th percentile of the ratio C). Equation (3) does the same but with a threshold equals to .21 (median of the ratio C) and equation 4 for .11 (25th percentile of ratio C).
Finally, Panel B replicates the exercise but with a different ratio M= $\frac{\text{Number of projects in basin j for firm i}}{\text{Total number of project in basin j}}$. The intuition of panel B is to drop projects in basins where the PE backed firm accounts for a large fraction of the local projects. The thresholds for M are 0.085, 0.046 as well as 0.01 and corresponds to the 75th, 50th and 25h percentile. Equation (1) drops projects located in basin(s) where M is above 0.085, equation (2) when M is above 0.046 and equation (3) drops all projects located in basin(s) where M is above 0.46.

Table A.3: Controlling for Confidential Reporting

Panel A: Baseline results and confidential reporting

	Dependent variable: Number of toxic chemicals							
	PE deal with control rights				Drillco (no control rights)			
	(1)	(2)	(3) NNM	(4) NNM	(5)	(6)	(7) NNM	(8) NNM
Post deal	-0.188***	-0.178***	-0.205***	-0.196***	-0.028	-0.041	-0.003	-0.034
	(0.054)	(0.055)	(0.036)	(0.038)	(0.045)	(0.048)	(0.042)	(0.043)
Controls	X	X	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X	X	X
Basin × Year FE			X	X			X	X
Location × Year FE	X	X			X	X		
Confidential		X		X		X		X
Adjusted R^2	0.56	0.57	0.35	0.37	0.55	0.57	0.45	0.49
Observations	135554	135544	21433	21423	135738	135728	28581	28575

Panel B: Natural experiment

	Dependent variable: Number of toxic chemicals							
	Net effect				Full interactions			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta	0.354***	0.285***	0.314***	0.252***	0.386***	0.316***	0.329***	0.257***
	(0.065)	(0.067)	(0.059)	(0.059)	(0.089)	(0.087)	(0.085)	(0.082)
Observations	135738	135257	135728	135246	135738	135257	135728	135246
R^2	0.60	0.67	0.61	0.68	0.60	0.67	0.61	0.68
Controls	X	X	X	X	X	X	X	X
Firm × Year FE		X		X		X		X
Firm FE	X		X		X		X	
Location × Year FE	X	X	X	X	X	X	X	X

Note: Panel A contains the baseline specifications where the number of confidential items reported is taken into account. Columns (1), (3), (5) and (7) adds the total number of confidential items reported for a well as a linear control. Columns (2), (4), (6) and (8) include a dummy for each number of confidential items. Column (1), (2) (4) and (5) are estimated on the full sample, whereas column (3), (4) (7) and (8) use the matching sample. Columns (1) to (4) measure the impact of PE ownership, whereas columns (5) to (8) evaluate the effect of PE DrillCo. Panel B contains regressions that perform the same exercise on the natural experiment. Beta stands for the coefficient: Federal or Native American reservations well × Post deal × Post Injunction. The dependent variable is the number of toxic chemicals. Column (1) to (4) are estimated when only the interaction is specified. Column (5) to (8) presents the results where the full interactions is made, as in a triple difference-in-differences. Columns (1), (3), (6) and (7) contains a firm FE, that is interacted with a year-FE in column (2), (4), (6) and (8). Column (1), (2), (5), and (6) include as a control the number of confidential items reported, and column (3), (4), (7) and (8) include this number as a fixed effect.

Table A.4: Role Of Confidential Reporting

Panel A: Impact on confidential reporting (net effect)

	Dependent variable: Number of inputs reported as confidential					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post deal	-4.328***	-4.317***	-3.420***	-4.316***	-4.327***	-4.798***
	(0.635)	(0.630)	(0.695)	(0.788)	(0.778)	(0.854)
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Basin × Year FE			X			X
Location × Year FE	X	X		X	X	
Adjusted R^2	0.61	0.61	0.57	0.61	0.61	0.46
Observations	135554	135554	21433	135554	135554	28581

Panel B: Impact on confidential reporting (Natural experiment)

	Dependent variable: Number of inputs reported as confidential			
	(1)	(2)	(3)	(4)
Federal or Indian well × Post deal × Post Injunction	0.994	0.992	0.205	0.213
	(0.817)	(0.814)	(0.996)	(1.000)
Controls		X		X
Firm × Year FE			X	X
Firm FE	X	X		
Location × Year FE	X	X	X	X
Observations	135738	135738	135257	135257
Adjusted R^2	0.61	0.61	0.66	0.66

Note: Columns (1), (2) and (3) of Panel A report the impact of PE ownership on the total number of confidential items reported and columns (4), (5) and (6) of Panel A study the impact of PE financing through DrillCo on the same outcome variable. Column (1) and (4) estimate the relationship without controls, that are added in column (2) and (5). The coefficients remain stable when the controls are added. Column (3) and (6) contain the results when the relationship is estimated on the matched sample using a nearest neighbor matching (NNM) approach, both before and after the deal at the project level. The matched sample is constructed as follow: for each project that belongs to a firm that is acquired by a PE, we matched within the same geographical area (basin) and year, the project that has the closest size (horizontal length and vertical depth) and production (6 first months production of oil and gas). Standard errors are clustered at the firm level. Panel B investigates the impact of BLM fracking rule preliminary injunction and subsequent rescind in a triple difference-in-differences on the number of confidential items reported. Specifically, the dependent variable is regressed on all the interactions between the post acquired dummy, a dummy for wells in federal lands or Native American reservations and a dummy for the period between. Only the triple coefficient is reported. Column (1) and (3) do not include time-varying controls, that are added in column (2) and (4). The controls are the same as the one used in Panel A. Column (1) and (2) report the results with a location and year FE as well as a firm FE. Column (3) and (3) add a year FE interacted with a firm FE.

Table A.5: Controlling For Population And Housing Density In The Baseline Results

Panel A: PE ownership and control

	Dependent variable: Number of toxic chemicals					
	(1)	(2)	(3)	(4) NNM	(5) NNM	(6) NNM
Post deal	-0.198***	-0.198***	-0.198***	-0.209***	-0.209***	-0.212***
	(0.054)	(0.054)	(0.053)	(0.036)	(0.035)	(0.035)
Observations	135554	135554	135554	21433	21433	21433
Controls	X	X	X	X	X	X
Firm FE	X	X	X	X	X	X
Location × Year FE	X	X	X	X	X	X
Housing FE			X			X
Population FE			X			X

Panel B: PE financing (DrillCo)

	Dependent variable: Number of toxic chemicals					
	(1)	(2)	(3)	(4) NNM	(5) NNM	(6) NNM
Post deal	-0.037	-0.037	-0.038	-0.022	-0.020	-0.020
	(0.046)	(0.046)	(0.046)	(0.048)	(0.049)	(0.047)
Observations	135554	135554	135554	28581	28581	28581
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Location × Year FE	X	X	X	X	X	X
Housing FE			X			X
Population FE			X			X

Note: Panel A replicates the baseline results where housing and population of the census tract where the well is located are added as controls. Column (1) and (4) adds the control in a linear way. Column (2) and (5) add the controls by adding all interactions of the two variables and their squared values. Column (3) and (6) add a decile fixed effect of the controls. Regressions from columns (1) to (3) are estimated on the full sample and columns (4) to (6) on the matched sample. Panel B has the same structure, except that the post variable takes the value 1 after a DrillCo deal.

Table A.6: Controlling For Population And Housing Density In The Natural Experiment

Panel A: Natural experiment (net effect)

	Dependent variable: Number of toxic chemicals					
	(1)	(2)	(3)	(4)	(5)	(6)
beta	0.346***	0.275***	0.346***	0.275***	0.346***	0.274***
	(0.066)	(0.064)	(0.066)	(0.064)	(0.066)	(0.065)
Observations	135738	135257	135738	135257	135738	135257
Controls	X	X	X	X	X	X
Firm $\times$ Year FE		X		X		X
Firm FE	X		X		X	
Location $\times$ Year FE	X	X	X	X	X	X
Housing FE					X	X
Population FE					X	X

Panel B: Natural experiment (full interaction)

	Dependent variable: Number of toxic chemicals					
	(1)	(2)	(3)	(4)	(5)	(6)
beta	0.383***	0.309***	0.383***	0.309***	0.382***	0.308***
	(0.090)	(0.084)	(0.090)	(0.084)	(0.090)	(0.084)
Observations	135738	135257	135738	135257	135738	135257
Controls	X	X	X	X	X	X
Firm $\times$ Year FE		X		X		X
Firm FE	X		X		X	
Location $\times$ Year FE	X	X	X	X	X	X
Housing FE					X	X
Population FE					X	X

Note: Panel A and B contains the estimations of the natural experiment. Panel A reports the net effect when only the triple interaction term beta is included, and panel B reports the triple difference-in-differences estimates where all the intermediary interactions are included. Beta stands for the coefficient Federal lands or Native American reservations \$\times\$ Post deal \$\times\$ Post Injunction. Column (1) and (2) add the control housing and population density of the census tract where the well is located in a linear way. Column (3) and (4) add as a control the full interaction terms with their square value to capture any non-linearity effect. Finally, column (5) and (6) add the decile of housing and population density as a fixed effect. Column (2), (4), (6), (8) include a firm interacted with a year fixed effect and column (1), (3), (5) and (7) a firm fixed effect.

Table A.7: Sorting on population

Panel A: Baseline effect

	PE ownership				PE drillco			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post deal	-2.114	-2.088	-1.164*	-1.149*	-1.160	-1.313	0.018	-0.037
	(1.681)	(1.684)	(0.665)	(0.667)	(2.683)	(2.701)	(1.025)	(1.031)
Controls		X		X		X		X
Firm × Year FE								
Firm FE	X	X	X	X	X	X	X	X
Location × Year FE	X	X	X	X	X	X	X	X
Observations	135738	135738	135738	135738	135738	135738	135738	135738
Adjusted R^2	0.51	0.51	0.53	0.53	0.51	0.51	0.53	0.53

Panel B: Natural experiment

	Dependent variable: population				Dependent variable: housing			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Beta	6.274	5.405	8.804	8.414	2.635	2.100	3.776	3.612
	(8.208)	(6.767)	(7.889)	(7.084)	(3.522)	(2.821)	(3.399)	(2.956)
Controls	X	X	X	X	X	X	X	X
Firm × Year FE		X		X		X		X
Firm FE	X		X		X		X	
Location × Year FE	X	X	X	X	X	X	X	X
Observations	135738	135257	135738	135257	135738	135257	135738	135257
Adjusted R^2	0.51	0.52	0.51	0.52	0.53	0.54	0.53	0.54

Note: Note: Panel A investigates whether PE-backed firms locate their wells in less populated area. The dependent variable is the total population in the census tract for columns (1), (2), (5) and (6) or the total number of housing units for columns (3), (4), (7) and (8). Column (1), (3), (5) and (7) don't contain controls that are added in columns (2), (4), (6) and (8). Columns (1) to (4) estimate the relationship for PE contracts where there is a transfer of controls. Columns (5) to (8) estimate the relationship for DrillCo contracts.
Panel B investigates the effect of the BLM shock for PE-backed firms on the population and housing density where the well is located. Beta stands for . The dependent variable of columns (1) to (4) of Panel B is the total population of the census tract where the well is located. The dependent variable of columns (5) to (8) of Panel B is the number of housing units in the census tract where the well is located. Columns (1), (3), (5), (7) include a firm fixed effect that is interacted with a year fixed effect in columns (2), (4), (6) and (8). Columns (1), (2), (5) and (6) report the net effect. The triple difference-in-differences effect are contained in columns (3), (4), (7) and (8). Standard errors are clustered at the firm level.

Table A.8: Impact Of PE On Pollution: Other Definition Of Toxicity

Panel A: Net effect

	Dependent variable: Number of toxic chemicals (EPA definition)					
	PE deal with control rights			Drillco (no control rights)		
	(1)	(2)	(3) NNM	(4)	(5)	(6) NNM
Post deal	-0.089***	-0.089***	-0.080***	0.028	0.027	0.033
	(0.021)	(0.021)	(0.023)	(0.031)	(0.031)	(0.041)
Observations	135554	135554	21433	135738	135738	28581
Controls		X	X		X	X
Firm FE	X	X	X	X	X	X
Basin × Year FE			X			X
Location × Year FE	X	X		X	X	

Panel C: Natural experiment

	(1)	(2)	(3)	(4)
Beta	0.172***	0.172***	0.121***	0.121***
	(0.047)	(0.047)	(0.030)	(0.030)
Controls		X		X
Firm × Year FE			X	X
Firm FE	X	X		
Location × Year FE	X	X	X	X
Observations	135554	135554	135071	135071
Adjusted R^2	0.80	0.80	0.82	0.82

Note: The dependent variable is the number of toxic chemicals used in the production process, where the toxicity is defined in another way as in the baseline regression. Columns (1), (2) and (3) report the impact of PE ownership on pollution and columns (4), (5) and (6) study the impact of PE financing through DrillCo contracts on pollution. Column (1) and (4) estimate the relationship without controls, that are added in column (2) and (5). The coefficients remain stable when the controls are added. Column (3) and (6) contain the results when the relationship is estimated on the matched sample using a nearest neighbor matching (NNM) approach, both before and after the deal at the project level. The matched sample is constructed as follow: for each project that belongs to a firm that is acquired by a PE, we matched within the same geographical area (basin) and year, the project that has the closest size (horizontal length and vertical depth) and production (6 first months production of oil and gas).

Table A.9: Pollution For Public Listed Firm

	Effect of going public			Earnings forecasts	
	(1)	(2)	(3)	(4)	(5)
Post IPO	0.140*	0.141*	0.275*		
	(0.077)	(0.077)	(0.143)		
Before IPO			0.210		
			(0.211)		
Under estimate				0.062***	0.062***
				(0.022)	(0.022)
Over estimate				-0.011	-0.012
				(0.088)	(0.088)
(mean) actual				-0.013	-0.013
				(0.012)	(0.012)
Observations	135724	135724	135724	53411	53411
Controls		X	X		X
Firm FE	X	X	X	X	X
Location $\times$ Year FE	X	X	X	X	X

Note: Equations (1), (2) and (3) estimate the impact of going public on the usage of toxic chemicals. Relying on the Field-Ritter dataset, I identify 7 IPO between 2011 and 2019 that can be matched to the sample: (1) Athlon Energy (2) Bonanza Creek Energy (3) Diamondback Resources (4) Extraction oil & gas (5) Jagged Peak Energy (6) Kinder Morgan and (7) RSP Permian. Post IPO is a variable that takes the value one after the firm went public. Similarly, Before IPO is a variable that takes the value one three years before the IPO. Equations (4) and (5) investigate the magnitude of missing the one-year EPS forecasts by analysts on the usage of toxic chemicals. The controls are defined as in the previous specifications and include the realized EPS.

Table A.10: Negative Premium Of Environmental Liability Risks On Project Transactions

	(1)	(2)	(3)	(4)	(5)	(6)
Toxic chemicals	-0.417***	-0.365**	-0.249*	-0.376**	-0.300*	-0.466
	(0.154)	(0.157)	(0.142)	(0.158)	(0.156)	(1.033)
Observations	987	987	986	942	871	193
Deal type FE			X	X	X	X
Basin FE					X	X
Latitude - Longitude unit FE				X	X	X
Buyer FE						X
Seller FE						X