Fracking, Toxics, and Disclosure

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Abstract

Where are the boundaries of firms' voluntary self-regulation? An increasingly popular and seemingly low-cost regulatory approach is to simply require firms to disclose private information and count on public scrutiny to motivate a race to higher-quality practices. This "information-based" approach evidently leads to superior performance in domains from restaurant hygiene to renewable energy generation—but virtually all such evidence is from settings where the information is relatively accessible to laypeople, and most pertains to consumer-facing industries. I analyze the effect of disclosure regulations on firms' use of toxic additives in hydraulic fracturing, a non-consumer-facing industry rife with highly technical reporting. I exploit differences in the timing of state-level disclosure regulations to estimate a causal effect and infer pre-regulation chemical use from prior voluntary reports. I find these regulations resulted in a large and persistent decrease in toxic chemical use, demonstrating that disclosure policies operate through multiple mechanisms and can alter firms' choices even when consumer pressure is minimal and information is not easily interpretable.

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JEL codes: L51, L71, Q35, Q38, Q53, Q58

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1 Introduction

Information-based regulations are increasingly common in regulatory policy. In contrast to command-and-control regulation that prescribes or proscribes particular technologies or practices, and market-based regulations that directly modify agents' incentives via price effects, these policies simply require actors such as firms to disclose information that could plausibly affect the welfare of stakeholders, decreasing information asymmetries. The factors that explain increased use of information-based regulation suggest it will become more prevalent in coming years. These include technological advances in computing and data storage which make information cheaper to collect, store, and process, as well as the political economics of regulation: in a contentious political environment, elected officials may face lower political costs if they adopt regulations that merely require disclosure, compared to more costly alternatives. Further, prescriptive regulation such as bans on specific substances or processes may suppress innovation, especially in the context of emerging technologies. In this context disclosure offers an opportunity to "wait and see" while also allowing regulators to gather more information about issues of concern.

These factors have led to the use of information-based regulations in a wide range of industries, from financial regulation to food safety, in many countries. They are most commonly used in, and most of the research on their effects has focused on, consumer-facing industries (Fung et al., 2007). While prior research demonstrates that consumer-facing firms may alter behavior in response to disclosure requirements, firms that provide outputs in commoditized intermediate product markets may not respond similarly. Further, most prior research documents the effects of policies that make information relatively digestible to non-specialists, and policies that result in a single annual disclosure event, such as an annual inventory of toxic chemical releases representing a large number of firms at once. It is well established that the legibility and accessibility of information affects firms' response (Fung et al., 2007); in this context, analyzing the effects of disclosure regulations under very different conditions contributes to understanding how and when they influence firms' behavior.

This paper examines the effects of mandatory disclosure regulations on the chemicals that firms use in hydraulic fracturing for producing oil and gas from shale formations—a

technological advance in increasingly common use in the US in the late 2000s and early 2010s, and allowed firms to produce oil and gas from geologic formations previously considered uneconomical. The process requires injecting millions of gallons of slurry into the earth, including 50,000 to 100,000 gallons of chemicals, some of which may be toxic to humans and ecosystems (Stringfellow et al., 2014). Public and regulatory concerns about the use of toxic chemicals in the production process, among other things, were exacerbated by the widespread use of the technology in proximity to residential and commercial areas and a few high-profile spills. Firms successfully resisted federal regulations that would have required chemical disclosures, but many US states eventually passed laws requiring the same—virtually identical laws across states, often using common text. Prior to these laws, some operators also voluntarily disclosed chemicals used in some or all of their fractured wells, predominantly through a web-based database created by an industry council. The voluntary disclosures contain essentially the same information as the legally required reports.

I compare the chemical mixtures used before and after mandatory disclosure laws, using a difference-in-differences framework motivated by the differences in state-level regulatory timing. Pre-regulation chemical use is measured by the data voluntarily reported by some firms for some wells. Because the voluntary reports represent an incomplete sample of wells fractured prior to mandatory disclosure, the measured difference-in-differences is a composite of a full-reporting effect (chemicals used in wells that firms would not have voluntarily chosen to report) and a disclosure-pressure effect (the effect, if any, of mandatory disclosure on chemical choices). I show that under reasonable assumptions the net effect of full reporting is weakly positive, and verify this empirically by exploiting a unique regulatory episode in which complete chemical information is observed prior to public disclosure. This implies that a difference-in-differences estimate of the composite effect underestimates the magnitude of the disclosure-pressure effect. To estimate the disclosure-pressure effect more precisely, I run a separate analysis limited to wells operated by "frequent voluntary reporter" firms (those that voluntarily reported a large proportion of wells before mandatory disclosure), for whom the full-reporting effect is, mechanically, smaller in magnitude.

The analysis suggests that firms reduced the use of toxic chemicals in response to mandatory disclosure regulations, with persistent and statistically significant decreases beginning

about nine months after regulations and continuing for at least three years after. Moreover, the magnitude of the effect is relatively large, ranging from a 37% to 59% decrease in relative toxicity and a 68% to 84% decrease in the use of priority toxic and regulated chemicals. There is also a decrease, eventually, in firms' use of chemicals that are frequently mentioned by media as potentially dangerous or toxic, on the order of 45% to 76%—but this effect is slower to appear, starting about 8 or 9 quarters after regulations.

This paper makes several contributions. First, it presents a rigorous empirical analysis of the effects of mandatory disclosure in a non-consumer-facing industry, and in a setting where the information disclosed is both diffuse (spread out over time and difficult to compare across firms) and highly technical (lacking a ranking system or metric that facilitates understanding by non-experts). Much of the prior literature on the effects of information disclosure focuses on relatively accessible information within consumer-facing sectors, like restaurant hygiene grades (Jin and Leslie, 2003), drinking water quality violations (Bennear and Olmstead, 2008), and renewable energy generation among residential electricity providers (Delmas et al., 2010). Some studies have analyzed effects in non-consumer-facing sectors, like toxic releases among manufacturing firms (Khanna et al., 1998; Doshi et al., 2013), but the disclosures in these settings are easier for non-experts to interpret (quantities of toxics are clearly identified) and to access (data for many firms is released in a single, well-publicized annual report, and cross-firm comparisons are straightforward). By showing that disclosure can influence firm behavior even in conditions where public influence is relatively weak—since firms sell into intermediate markets, the timing of disclosures is diffuse, and reports are difficult for non-experts to access and interpret—this paper helps to elucidate the settings in which information-based regulations affect firms' behavior, and the mechanisms by which these regulations have influence.

Second, the analysis demonstrates a method, perhaps useful in other contexts, for estimating a treatment effect using a differences-in-differences method when pre-treatment data are incomplete. Although I observe just a subset of pre-disclosure outcomes of interest, I demonstrate that under reasonable assumptions the estimated effect of regulation is conservative, and use data from a unique regulatory episode to provide empirical support for those assumptions. Differences-in-differences typically relies on complete data in the pre-treatment

period, making analysis in some settings challenging or impossible. In principle, the method presented here could be used in other settings (albeit perhaps most likely in other analysis of disclosure regulations, where data prior to mandatory disclosure are typically hard to obtain).

Finally, this paper contributes to a growing literature on the phenomenon of hydraulic fracturing, an emerging technology that has transformed energy production in the U.S. and the world. Hydraulic fracturing has contributed to substantial economic growth, employment, and local government revenues (Hausman and Kellogg, 2015), even as it has raised concerns regarding local economic impacts and averting behavior (e.g. Muehlenbachs et al., 2015; Wrenn et al., 2016; Kirkpatrick and Fetter, 2018) and environmental and health impacts (e.g. Olmstead et al., 2013; Stringfellow et al., 2014; Konschnik and Dayalu, 2016; Hill and Ma, 2017). A substantial amount of public, regulatory, and scholarly concern has centered on the chemicals used in the fracturing process; this paper is the first to rigorously analyze the causal effects of disclosure policies (or any regulations) on the use of these chemicals.

The following section provides background on the empirical setting and discusses related literature. Section 3 describes the data, and Section 4 documents empirical methods. Section 5 presents results and robustness checks, and Section 6 concludes.

2 Background

2.1 Hydraulic fracturing

The US shale boom has dramatically altered global energy markets and has brought jobs, royalties, and tax revenues to nearby communities (Hausman and Kellogg, 2015). At the same time, environmental groups have raised concerns about aspects of the production process, including the use of toxic chemicals in the slurry of water, sand or other granular material ("proppant"), and a cocktail of chemical additives. Hydraulic fracturing involves injecting this fluid into formations hundreds or thousands of meters below the earth's surface. The chemicals enhance the productivity of water and proppant in many ways, including manipu-

lating fluid viscosity, enhancing natural fractures, carrying proppant deep into fractures, and minimizing bacterial growth in metal pipe casing. Firms have invested considerable research into optimal fluid designs, with toxicity as one consideration among many (Montgomery, 2013; Gulbis and Hodge, 2000). Industry practitioners indicate the choice of specific individual components is rarely driven by cost, because the cost of the chemicals themselves is small in comparison to the overall cost of the fracturing and stimulation operation.

While the chemicals used are typically a small proportion of fracturing fluid, they have still raised substantial public and regulatory concerns due to several factors: the large absolute volume of chemicals per well (on the order of 100,000 gallons of chemicals for a typical fracture using 5 million gallons of slurry), the temporal and spatial concentration of fracturing during the height of the boom, the proximity of some wells to non-industrial land uses, and a few high-profile incidents of water pollution that some reports linked to fluid spills. In addition, early media coverage highlighted both the toxicity of some chemicals used and the industry's desire to keep chemicals secret (e.g. Elgin et al., 2012; Haas et al., 2012).

2.2 Regulatory setting

In the United States, the Environmental Protection Agency (EPA) regulates subsurface injection through the Underground Injection Control (UIC) provisions of the Safe Drinking Water Act (SDWA), which would require firms to identify certain characteristics of fracturing fluids. However, the 2005 Energy Policy Act exempted hydraulic fracturing from these provisions, except for fracturing fluids that contain diesel fuel.[1] Subsequent attempts to require firms to disclose chemical contents of fracturing fluids were met with resistance from firms, which cited proprietary concerns and argued that the compounds are not harmful when properly handled. A Congressional investigation in 2010-2011 identified many instances in which companies did not know the chemical makeup of compounds they were using (Waxman

[1]The EPA declined to regulate hydraulic fracturing under SDWA from its original date of passage (1974) based on the argument that underground injection was not the "principal purpose" of hydraulic fracturing. This policy was overturned after a 1997 ruling by the U.S. Court of Appeals for the Eleventh Circuit which, though limited to the use of hydraulic fracturing in coalbed methane production in Alabama, highlighted the debate over the applicability of SDWA. The 2005 Energy Policy Act included an amendment to SDWA that clarified the definition of "underground injection" in the SDWA in a way that excludes hydraulic fracturing—a clarification that some observers dubbed the "Halliburton Loophole" (Vann et al., 2014).

et al., 2011) and, in the wake of that report, individual states began to pass legislation that required companies to disclose the chemical additives used in their fluids.

Table 1 provides a timeline of state laws for public disclosure of fracturing fluid chemicals. Of the 18 states with significant fracturing activity and required public disclosure, about a third require operators to report information to the state regulator, a third to an industry-backed registry (FracFocus.org), and a third allow operators to choose. Despite some differences in reporting registry, state laws have quite similar requirements for what must be reported, including chemical name, chemical abstract service (CAS) number, the concentration in fluid (typically the maximum concentration in any fracturing stage), supplier name, and trade name if applicable. State laws also allow firms to avoid reporting chemical name and CAS number for additives that firms consider confidential or proprietary, but to activate this provision operators must typically file an affidavit for each such chemical (and still must disclose the quantity used). Some states also require operators to report the associated chemical family.

[Table 1 about here.]

State-level disclosure laws are virtually the sole regulation that applies to fracturing fluids (in part because of other exemptions from federal laws provided for under the 2005 Energy Policy Act). UIC laws apply only to the extent that when firms use diesel fuels in fluid they must obtain a permit in advance, and the definition of "diesel fuel" for this purpose remained nearly identical over the period studied here.[2]

2.3 Related literature

Bennear and Olmstead (2008) identify three mechanisms through which disclosure might result in abatement. The first is through the market: For instance, if consumers have information about firms' environmental performance and prefer greener goods, then they can exert market pressure in hopes of inducing firms to improve. Market mechanisms could

[2]In May 2012 EPA issued draft guidance for UIC permit writers to clarify the definition, but noted that permit writers should continue to use existing, pre-2012 regulations until final guidance was issued, which was in February 2014 (USEPA, 2012a, 2014). The definition in the final guidance was virtually identical to that in the draft, differing by only one chemical.

also operate through other channels, such as by higher financial or legal liabilities for firms engaged in dirtier production practices. The second mechanism is political: information may increase the ability of a concerned public to lobby for stronger regulation. Finally, disclosure may affect an organization's internal decision making, as individuals within the firm change their behavior as a result of measuring and reporting data.

As noted, some empirical analyses have been conducted on the effectiveness of disclosure policies using methods that can accurately identify causal effects. Most of this evidence is from industries where the information disclosed is of relatively high visibility to consumers, including electricity (Delmas et al., 2010; Kim and Lyon, 2011), drinking water (Bennear and Olmstead, 2008), and restaurant hygiene (Jin and Leslie, 2003). Analyses within industries that are less consumer-facing, such as manufacturing facilities that report to the Toxics Release Inventory (TRI), find that releases of reportable toxic chemicals have declined over the course of the program by as much as 50 percent (Bennear and Coglianese, 2005). However, because no data were available on toxic releases prior to the start of the program, this decrease cannot be definitively attributed to the public disclosure requirement (Bennear and Olmstead, 2008).

There has been no comprehensive empirical investigation of which mechanisms are most powerful or effective. Bennear and Olmstead (2008) note that in their setting, the market mechanism is likely not relevant since water suppliers are essentially monopolists, and the internal mechanism is unlikely to play a large role because of pre-existing monitoring requirements. Thus, they conclude the political mechanism drives the results in their study. Doshi et al. (2013) investigate the internal mechanism in depth by identifying what characteristics of firms influence or moderate their response to disclosure regulations, but they do not rule out the possibility that consumer or political pressure are also acting simultaneously to influence firms' decisions.

Indeed, cleanly isolating the operation of one particular mechanism is likely not possible without a case study of a particular (small) set of firms. For analysis on a larger group, the relative importance or effectiveness of different mechanisms is best teased out by analyzing the effects of disclosure regulations that operate in different settings, and noting which mechanisms are most likely to be relevant within those settings. This will help public decision

makers to identify the potential for information-based regulations to have desirable results, and conceivably to design effective public policy. This should be especially important as disclosure regulations become more prevalent in non-consumer-facing industries, where the market mechanism is less influential. It may also be more important in contentious or fractured political environments in which political channels are less effective because the threat of regulation is less credible.

3 Data

I create a novel data set with information about well completions, including chemical constituents of fracturing fluids, for 73,211 wells across seven states fractured between 2011 and 2015. To my knowledge, mine is the single most comprehensive dataset on fracturing chemicals. It includes information from what FracFocus calls its "version 1.0", when the site provided fluid reports only as individual PDFs on a site that was set up to resist scraping. At the time, text on the website noted the explicit intent to provide access to information about individual wells but not enable comparisons across a large number of wells. When FracFocus released its "version 2.0" in mid-2015, it provided a downloadable database to facilitate comparisons, but excluded many wells fractured prior to April 2013. I am able to include the "version 1.0" data because Skytruth, an NGO, successfully scraped that data and enabled public download of the results (Skytruth, 2013). In addition to combining the "1.0" and "2.0" versions of FracFocus data, I also incorporate information from the California state registry, which was an optional reporting site for operators in that state as of 2014 and required as of 2016.

In addition to chemical use, I incorporate data on well completions from all states in the study, which allows me to measure the degree of voluntary reporting prior to mandatory disclosure, as well as to determine permit dates for wells in states where the disclosure law effective date depends on the date of the drilling permit date rather than the date of the fracture. I also add information about chemical characteristics including toxicity. The following sections describe the data sources in more detail.

3.1 Chemical additives

Data on chemical additives comes from the FracFocus database (Ground Water Protection Council and Interstate Oil and Gas Compact Commission, 2015) and one state regulatory agency (California) that has comparable and accessible data. For the seven states in my analysis, FracFocus is the legally required reporting registry for operators in five: Colorado, North Dakota, Pennsylvania, Texas, and Utah.[3] I also include FracFocus reports from Oklahoma; operators there can choose to report the state rather than FracFocus, but state law indicates that regulators will then upload any such reports to FracFocus. Data for California come from both the Division of Oil, Gas and Geothermal Resources (DOGGR) and FracFocus.

The seven states in my analysis represent the great majority of wells fractured during the time of the study, but some fracturing did occur in other states—most notably, in Wyoming.[4] I attempted to compile chemical reports from other states but found substantial heterogeneity in the availability and accessibility of data. Some states post disclosure reports online, but use reporting formats that are variable and inconsistent, even within the same state and time period. Chemical information is frequently provided alongside other aspects of well completion in documents that number dozens of pages per well and are not conducive to machine reading. Available data from other states also tend to differ from FracFocus data, e.g., providing the name of a commercial substance but excluding information on specific chemicals. By focusing on states that use FracFocus or comparable state registries, I increase the internal validity of the results reported here, at the cost of some external validity: the effects I observe may not hold in states where chemical disclosures are even less accessible.

Initially, I identify 80,190 wells with chemical information. I drop 3,244 of these for one of three reasons: (i) there is insufficient information to classify them as voluntary or mandatory reports, (ii) there is no information on covariates (water volume, depth, oil/gas), or (iii) data entry or data scanning errors make the chemical concentration information

[3] It is also the required registry for wells in Alabama, but there were very few wells there during the study period (126) and only a handful of these meet the criteria for usable observations.

[4] Based on my attempts to scrape fluid reports from the Wyoming DEQ website, there appear to be about 3,000 wells subject to disclosure requirements there during my study period, which amounts to less than 5% of the wells in my final sample.

uninterpretable (e.g., when the recorded concentration of an ingredient exceeds 100 percent, or the sum of concentrations is far lower or higher than 100 percent). I remove an additional 3,735 wells fractured before or after the time cutoff values shown in equation (3), the time-varying difference-in-differences econometric specification (i.e., more than 6 quarters prior to the regulation, or more than 12 quarters after). These observations would drop out of the estimation of equation (3) in any case, and excluding them from the estimation of (1) and (2) makes for comparable results. I have run the analyses including these observations (for equations (1) and (2)), and the results are essentially identical to those reported below.

3.2 Chemical characteristics

Companies use nearly 2,000 distinct additives in fracturing fluid; individual wells typically use 10 to 40 chemicals. I calculate four well-level measures of fluid toxicity and run separate analyses for each.

The first measure, "priority toxic and regulated chemicals" (PTRCs), is the total concentration of chemicals that fall into any of four groups. Three of these groups correspond to regulatory classification: (i) regulated as primary contaminants by the Safe Drinking Water Act; (ii) regulated as Priority Toxic Pollutants for ecological toxicity under the Clean Water Act; or (iii) classified as diesel fuel under EPA guidance on fracturing operations (USEPA, 2012a, 2014). The fourth group includes chemicals listed in the USEPA Risk-Screening Environmental Indicators (RSEI) database (USEPA, 2012b) as having a relatively high toxicity value for chronic human health effects from oral exposure.[5]

The second measure is the weighted sum of concentrations of individual chemicals in fracturing fluid, with weights corresponding to chronic human health toxicity scores from RSEI (USEPA, 2012b). Unlike the first measure, which is simply a sum of concentrations, this provides a toxicity-adjusted measurement of chemicals of potential concern within the fluid. Still, it is limited to chemicals that have been analyzed for toxicity with sufficient rigor

[5]The RSEI database provides peer-reviewed relative toxicity scores and relative risk values for nearly 500 chemicals covered by the Toxics Release Inventory. Chemical-specific measures for toxicity are based on detailed, peer-reviewed evaluations from oral and inhalation exposure pathways (separately). Among chemicals used in fracturing fluid, toxicity scores range from 0.5 (formic acid) to 3,000,000 (hydrazine and quinolone); these are unitless scores that are intended to provide order-of-magnitude comparisons. For this analysis, PTRCs include any chemicals that have a toxicity score of at least 200.

and peer-review to be included in the RSEI database. Some chemicals of potential concern that are used in fracturing fluid may not be included in RSEI or covered by water quality regulations, an issue that Stringfellow et al. (2014) discuss in some detail.

The third measure addresses the use of chemicals that are frequently cited in media reports in association with potential dangers of fracturing, regardless of regulatory status or scientific evidence of toxicity. I use this metric to test the possibility that companies respond more to public concern or media attention than to toxicity or regulatory status. I identify "high media profile" chemicals by searching for media reports that mention particular chemical names in conjunction with fracturing and words indicating danger or hazard, and designate chemicals as high-profile if they were mentioned in at least 100 distinct media stories over a five-and-half-year period.[6] Like the first metric, this measure is the sum of reported concentrations of these "high media profile" chemicals.

Finally, I calculate a fourth measure that is the sum of concentrations of chemicals that firms designate as proprietary or confidential business information. This measure allows a test of whether disclosure laws resulted in an increase in companies' use or declaration of proprietary chemicals.[7] Unfortunately, the results for this metric are difficult to interpret since, although state disclosure regulations have relatively similar provisions for reporting proprietary chemicals, in the voluntary reporting regime operator decisions to list proprietary chemicals appear to be heterogeneous.[8] The implication is that an observed increase in proprietary chemicals after disclosure laws could arise not from an actual increase in their use, but also because disclosure laws formalized the necessity to report proprietary chemicals in fluids.

Overall, I consider 790 distinct chemicals as "of potential concern," and I observe 64 of these in fracturing fluid. This includes 46 PTRCs, 13 high-media-profile chemicals, and 58 chemicals with positive relative toxicity scores from RSEI.

[6]These media reports typically describe the rapid spread of fracturing, the proximity of non-industrial land uses, offer a few specific environmental concerns, and list one or more chemicals in use in fracturing fluid. The substance mentioned most often is diesel (1,816 stories), followed by benzene (1,230) and toluene (491 stories).

[7]This could arise, for instance, if operators were concerned that disclosure laws would erode competitive advantage by forcing them to reveal trade secrets; see Fetter et al. (2018).

[8]This is supported by my conversations with operators as well as visual inspection of numerous voluntary disclosure forms.

3.3 State permitting databases

I supplement FracFocus data with information from state permitting databases (drawn primarily from DrillingInfo) and use this in two ways. First, in Texas, the disclosure law applies based on the issue date of the initial drilling permit, rather than the date of fracturing. The FracFocus data do not include initial drilling permit date, so I obtain these dates from the state regulatory database. Second, state permits allow the development of a "census" of wells that are completed, which represents the universe of wells that are either ready to fracture, in process of fracturing, or where fracturing has been performed, such that the well is ready to produce. Developing this universe of wells allows me to estimate precisely the degree to which each firm voluntarily reported fractures, prior to the mandatory requirement. I calculate a firm-level measure of voluntary reporting and use this measure to distinguish "voluntary reporters"—firms that reported chemicals for a high percentage of their wells prior to mandatory disclosure. This in turn helps to distinguish the effect of disclosure regulations from the full-reporting effect: the latter effect is smaller for voluntary reporter firms, since these operators already reported chemical use for a large proportion of their wells before mandatory disclosure.

I classify firms as voluntary reporters if they provided chemical reports for at least 75% of their horizontal wells in the 12 months prior to the regulation effective date in the relevant state. For instance, Range Resources completed 171 horizontal wells in Pennsylvania, Texas and Oklahoma in the 12 months leading up to the respective disclosure laws in those states. This firm filed chemical disclosure reports for 153 (89%), so I classify it as a voluntary reporter.[9]

3.4 Descriptive statistics

Table 2 provides a summary of locations and other information for the wells used in this analysis. For about one-quarter of the wells chemical information is voluntarily reported, while information is reported by law for the remaining three-quarters. The proportion of wells that are voluntarily reported is relatively stable across states, although somewhat lower

[9]The results shown are robust to alternative thresholds, from 50% to 90%.

in North Dakota (14%) and higher in California (54%) than other states, which range from 23% to 39%. Over half the wells are in Texas; Colorado contributes the next largest share of wells for an individual state, at 12%. Over half the operators work at least partially in Texas.

[Table 2 about here.]

Texas also passed the earliest mandatory disclosure law requiring reporting to FracFocus. Unlike other states, however, Texas used the date of issue for the drilling permit, rather than the date of the fracturing job, to determine legal reporting requirements. Thus, many of the 9,341 voluntarily reported wells (nearly half of those in my dataset) were fractured after February 1, 2012, when the Texas law came into effect. Because the operators of these wells obtained drilling permits prior to February 1, any chemical fluid reports I observe were voluntarily submitted.

Table 3 shows similar information but focuses on the subset of operators that voluntarily report chemicals for at least 75% of their horizontal wells in the year prior to mandatory regulation in the relevant state. About half the wells in my sample are fractured by these "VR75" operators, though the percentage of these wells varies by state (from 1% in California to 77% in Pennsylvania). Relatively few operators, just 8%, fall into the VR75 category, though they represent a disproportionate number of wells (47%).

[Table 3 about here.]

The relationship between operator size and voluntary reporting is worth investigating because my technique to distinguish the full reporting effect from the disclosure pressure effect relies on running the difference-in-differences analysis separately for the VR75 operators. If these are also the largest operators, I may not be able to distinguish a finding of a significant effect of disclosure regulations for VR75 operators from the effect on large operators. Table 4 shows that of the 25 largest operators (by number of wells), only half (12) are VR75; of the top 10 only 6 (albeit, including the top 5) are VR75. Thus, some but not all of the largest operators are VR75. Table 4 also shows which of the largest operators meet another VR-related classification, VR90, identifying firms that met a 90% (rather than

75%) threshold for voluntary reporting.[10]

[Table 4 about here.]

Table 5 provides descriptive statistics for the explanatory and dependent variables I use in my analysis. The average well in my sample is about 8,500 feet deep and uses slightly over 3 million gallons of water. About 61% of the wells in the sample are for oil (or combined oil and gas), and 39% are gas wells only. Of the 71,989 wells for which the well direction is known, 69% are horizontal or directional wells while 31% are vertical wells. The direction is not reported for 1,222 wells.

[Table 5 about here.]

The dependent variables, concentrations of various chemicals of interest, exhibit substantial right skew. To reduce the skewness I take logs (adding 0.01 so the log of zero values is defined), but even then there are some outliers which may have an undue influence on OLS coefficients. I therefore take the additional step of winsorizing these outliers, defined as values greater than $P75 + 1.5 * IQR$ or less than $P25 - 1.5 * IQR$, where IQR is the interquartile range and $P75$ and $P25$ represent the 75th and 25th percentile values, respectively. Table 5 shows summary statistics for these winsorized variables as logs; to facilitate interpretation, the table also shows summary statistics for the corresponding levels.

[Table 6 about here.]

Table 6 shows the mean and standard deviation for wells reported under each regime type (voluntary or mandatory), and differences between the means for each regime type. Voluntarily reported wells tend to be less deep, use less water, are more likely to be gas wells, and are slightly more likely to be vertical wells. They also tend to use lower log concentrations of PTRCs, high-media-profile chemicals, proprietary chemicals, and lower log relative toxicity scores. All of these differences are statistically significant, but not all are

[10]Since only one of the ten largest operators is a VR90 firm, analyzing the subset of VR90 firms allows me to better distinguish whether the toxicity-reducing effect of disclosure laws applies only to the largest operators. When I analyze the wells of VR90 operators—using an approach identical to that for VR75 operators—I find results qualitatively identical to those reported in section 5.

necessarily meaningful; the difference in mean depth, for instance, represents about a 2% shallower well, which is not likely meaningful.

However, to the extent that public and regulatory concern over fracturing inputs has focused on water and chemical use, the lower reported use of water and chemicals for voluntarily reported wells is consistent with the notion that companies tend to voluntarily disclose operations that may be seen as less controversial. Other explanations exist: other researchers have found companies using greater amounts of water per well as fracturing technology advances (Covert, 2015); thus, the lower water use may be simply due to the fact that voluntary reports tend to occur earlier in time. The greater observed use of chemicals of interest may be attributable to the full-reporting effect discussed previously.

4 Econometric approach

Ideally I would randomly assign mandatory disclosure to some wells and observe the use of toxic chemicals for all wells before and after assignment. Since I cannot manipulate policy, I motivate the empirical model as a natural experiment where states require disclosure at different times. I use a difference in differences specification that exploits variations in the effective dates of state regulations. In this section I document my econometric approach and address empirical models and identifying assumptions.

4.1 Empirical models

The basic model for the difference-in-differences approach is

$$Y_{ipjst} = \alpha_s + \lambda_t + \delta D_{st} + \gamma W_i + \theta_j + \psi_p + \sum_{p=1}^{P} \psi_p \times \lambda_t + \epsilon_{ijpst} \tag{1}$$

where Y_{ipjst} is the variable of interest (e.g., percent of toxic additives). Subscripts i, j, p, s, and t denote, respectively, well, operator, geologic play, state, and time. Thus α_s, λ_t, θ_j, and ψ_p represent fixed effects for state, time, operator, and geologic play, while W_{it} is a vector of well characteristics. The interaction of geologic play and time period controls for time-varying factors within each geologic play, including whether operators face

a mandatory reporting regulation within each play. That is, this interaction term controls for the assumption that operators implement toxics-reduction policies at the level of geologic play (not just within a state jurisdiction), which is consistent with the organizational structures of operators who work over broad geographic areas. The variable for treatment, D_{st}, takes the value one if disclosure was mandatory in state s in period t. Thus, δ represents the average difference-in-differences in toxic chemical use between the treatment and control groups, and if $\delta < 0$ then the use of toxics (or another measure of interest) declined as a result of the mandatory disclosure law.

This specification assumes a limited set of differences between the periods "before mandatory disclosure" and "after mandatory disclosure." These differences include the change in disclosure regulations as well as different operator decisions over the well parameters in W_{it}, the distribution of wells across geologic plays, and the involvement of individual operators. Still, operators could have experienced changes in managerial structure, or revised company policies in ways that altered the approach to fluid formulation, during the study period, for reasons independent of the change in disclosure laws. There could be also unobserved changes in state regulatory environments over time in ways that cause different responses of firms to existing regulations: for instance, changes in staffing levels, attention or focus of individual agencies or personnel, or updated reporting forms. In order to measure more precisely the effect of the disclosure law conditional on these time-varying, operator-level and state-level characteristics, I incorporate operator-year dummy variables and state-time trends. (Unfortunately using dummy variables at the state-time level would be collinear with the treatment, so instead I interact state dummy variables with an annual time trend.) The econometric specification is then:

$$Y_{ipjst} = \alpha_s + \lambda_t + \sum_{s=1}^{7} \alpha_s \times t + \sum_{j=1}^{J} \theta_j \times \phi_t + \delta D_{st} + \gamma W_i + \theta_j + \psi_p + \sum_{p=1}^{P} \psi_p \times \lambda_t + \epsilon_{ijpst} \quad (2)$$

This specification provides an improved focus on the effect of the regulation conditional on potentially confounding variables. However, it does not allow me to measure any differences in the effect of the regulation over time. To address this, I replace the single difference-in-

differences variable D_{st} with one that is allowed to vary over time, and measure the effect of the regulation 6 quarters prior and 12 quarters after the date the regulation becomes effective. Thus, this specification is

$$Y_{ipjst} = \alpha_s + \lambda_t + \sum_{s=1}^{7} \alpha_s \times t + \sum_{j=1}^{J} \theta_j \times \phi_t + \sum_{\tau=-6}^{12} \delta_\tau D_{st} + \gamma W_i + \theta_j + \psi_p + \sum_{p=1}^{P} \psi_p \times \lambda_t + \epsilon_{ijpst} \quad (3)$$

Equation (3) is identical to (2) except that D_{st} is an indicator equal to one if disclosure was mandatory in state s at time $t - \tau$. The δ_τ coefficients are the differences in differences corresponding to each time period. By plotting these δ_τ coefficients for each quarter, I can test for differences in the effect of the mandatory disclosure "treatment" over 18 months prior and 36 months following the treatment. I can also verify empirically whether the parallel trend assumption holds: that is, whether the pre-treatment differences between treatment and control are approximately zero.

To calculate standard errors and confidence intervals, I cluster standard errors at the state level, reflecting standard guidance for difference-in-differences (and other) analyses since the model residuals are likely not independent within groups (Angrist and Pischke, 2008; Bertrand et al., 2004). However, the usual procedure for estimating cluster-robust standard errors in OLS (White, 2000) relies on three assumptions for consistent estimates (Mackinnon and Webb, 2016), and two of those assumptions (large number of clusters, and "balanced" clusters with roughly equal numbers of observations) are likely violated in this setting, since I have just seven clusters and one includes about half of my observations. Furthermore, estimated standard errors are almost always too low when these assumptions are violated, leading to over-rejection of the null hypothesis. A number of alternative procedures have been suggested for consistent estimation of standard errors (Cameron et al., 2008; Cameron and Miller, 2015; Mackinnon and Webb, 2016). I implement two of these methods. The main results reported in Section 5 use the $G-1$ degrees of freedom correction, which amounts to a t-test with degrees of freedom equal to the number of clusters G minus one. Cameron and Miller (2015) advise this as an easily implemented approach that offers substantial improvements in consistency of estimates. As a robustness check, I also calcu-

late p-values using a wild cluster bootstrap, following the procedures in Cameron and Miller (2015) with one critical improvement that is little-known in empirical literature but essential for hypothesis testing when $G < 10$ or so (Webb, 2014; Mackinnon and Webb, 2016).[11]

4.2 Identifying assumptions for causal interpretation

The difference-in-differences model is a natural choice suggested by state-level differences in regulatory timing. To interpret δ as the causal effect of the regulation, three identifying assumptions are necessary. Two of these are common to difference-in-differences approaches: exogenous timing of the treatment and parallel trends prior to the treatment. The third is peculiar to my setting: the appropriateness of using voluntarily reported data to serve as the pre-treatment measure of behavior.

4.2.1 Exogenous timing of treatment

First, I assume the timing of treatment is exogenous. Given the historically close relationship between the U.S. oil and gas industry and its regulators, it is possible that regulators issued the mandatory disclosure requirement only after operators signaled preparedness, which presumably would occur only when they had minimized its toxic or controversial components. If this were true, it would imply the treatment is not random with respect to the variable of interest, and my estimate of the treatment effect would be biased (toward zero).

[11] The regular bootstrap involves resampling observations from the original sample, with replacement; in a cluster setting, this is applied as a block bootstrap in which the blocks are clusters. However, using Monte Carlo tests Cameron et al. (2008) show that this method does not eliminate over-rejection in settings with few clusters, and that the wild cluster bootstrap performs better with few clusters. Instead of sampling observations using pairs of right-hand-side and left-hand-side variables x, y, the wild cluster bootstrap involves calculating a new y^* equal to a predicted value of y plus a weighted residual, where the weights follow a specific random distribution. In the wild cluster, every observation in the original dataset is used exactly once in each bootstrap replication (Webb, 2014). Thus, the randomness that underlies the power of the bootstrap arises from the randomly weighted residual that is added to $\hat{y}$. This is unlike the regular bootstrap (better denoted a "pairs cluster," as Cameron et al. (2008) point out), in which the randomness arises from the fact that each observation in the original dataset may be drawn one or more times, or not at all. In a setting with very few clusters—as here—Cameron et al. (2008) and Cameron and Miller (2015) advise weighting the residual by a value chosen from the Rademacher distribution, which takes the values -1 and $+1$ with equal probability. Unfortunately the Rademacher weighting scheme produces at most 2^G different values, which makes hypothesis testing using the wild cluster bootstrap unreliable when $G < 10$ or so. Webb (2014) and Mackinnon and Webb (2016) demonstrate why a particular six-point distribution offers better results for small G. I use this "Webb" distribution in implementing the wild cluster bootstrap here.

Media reports from the relevant period, and my interviews with industry personnel, provide mixed evidence with respect to industry perspectives regarding chemical disclosure. On balance it seems that early industry opposition to disclosure gave way to acceptance of state laws for disclosure, at least in public statements, though the industry opposed proposed federal disclosure laws throughout this period. As noted in Section 2.2 the 2005 Energy Policy Act exempted hydraulic fracturing from EPA regulation under UIC provisions of SDWA; regardless of whether this represented a clarification or a loophole, the industry supported the exemption, removing obligations to disclose chemicals. The industry also opposed the Fracturing Responsibility and Awareness of Chemicals Act (FRAC Act), first proposed in the 111th Congress (2009-2010), which would have reversed the SDWA exemption and also required disclosure of fracturing fluid chemicals.

A Congressional investigation, begun in February 2010, provided the first public information on chemical use. The investigators found that many operators did not know what chemicals were used in their operations, nor did their contractors; rather, third-party manufacturers held the information as trade secrets. Waxman et al. (2011) concluded that "... it appears that the companies are injecting fluids containing unknown chemicals about which they may have limited understanding of the potential risks posed to human health and the environment." Also during 2010, New York became the first state to issue a moratorium on permits for hydraulic fracturing, in part due to concerns about chemical use. Perhaps realizing that regulation would come in some form, and evidently preferring state to federal regulation, when the first state regulations were passed in late 2010 operators and industry groups generally expressed nonchalance about the new state laws, and voiced confidence that they could meet disclosure provisions (Sider, 2010).[12]

This expressed acceptance of state disclosure laws continued as more states proposed and passed disclosure regulations. In April 2011 the GWPC and IOGCC opened the FracFocus registry, with support of industry actors, to facilitate disclosure of individual reports (though the registry did not facilitate comparative analysis, as noted in Section 3.1). However,

[12]Two industry members I spoke with also indicated that some operators may have welcomed the disclosure requirements because it would force vendors to disclose additional information to operators about chemical use, thus reducing asymmetric information that reduces operators' power in negotiations with vendors and suppliers. Yet this would not explain why operators opposed federal regulation, which would presumably have given them even greater power.

industry actors continued to oppose federal regulations that would have required disclosure, including the reintroduction of the FRAC Act in the 112th, 113th, and 114th (2015-16) Congress. Industry representatives also opposed disclosure provisions in two proposed federal regulations. These include a 2014 EPA proposal to require recordkeeping and reporting of fracturing chemicals under the Toxic Substances and Control Act and a BLM rule issued in 2015 (and struck down in 2016) that set standards for fracturing on federal lands.

One theoretical framework that explains the industry behavior with respect to disclosure regulations is that of Lyon and Maxwell (2004), who suggest that corporate environmental strategy is underlain by a dynamic political economy game, in which firms respond to or encourage some forms of regulation in order to forestall other forms that are expected to be more costly or onerous, or less strategically advantageous. In this case, industry may have acceded to state regulation requiring chemical disclosure because they believed it could help to assuage public and regulatory concern. This in turn may help forestall more stringent federal regulation and/or more restrictive local, state or federal regulations, such as bans, moratoria, or large setbacks from incompatible land uses. In this context, the timing of the state regulations appears exogenous given that firms opposed early attempts to require disclosure and backed off their opposition to state regulations only after the Congressional investigation that presaged potential federal action.

4.2.2 Parallel trends

The second identifying assumption is that events that affect fluid composition in the treatment states also affect the others. For instance, a state law banning the use of certain chemical additives or a price change that affects states differently could violate this assumption. Neither possibility seems plausible here. No chemical-specific bans were applied to fracturing fluid in any state during the period of study. Conditional on time, prices for chemical inputs are likely to be similar since chemicals travel through broad and efficient transportation networks, so the law of one price should hold. I use time fixed effects in all specifications, and I also specifically check whether the parallel trend assumption holds empirically by analyzing the difference in treatment versus control states for six quarters prior to the regulation (see equation (3)).

4.2.3 Use of voluntary reports

Using voluntary reports to measure chemical use before mandatory disclosure potentially introduces bias into the causal effect of the regulation. For well i fractured by operator j in state s and play p at time t before mandatory reporting, I observe Y_{ijpst} for a subset (potentially an improper subset) of all wells. In the empirical analysis I use fixed effects for operator and play, as well as for the interaction of operator-time and play-time, and thus—in what follows—I focus on variation in i, s, and t. The average quantity of toxics (or other chemicals of interest) across all wells in s, t is $\tilde{Y}_{st} = Y_{st} + \mu_{st}$, where μ_{st} represents the quantity of chemicals unobserved due to incomplete reporting. This introduces a complication into the difference-in-differences estimate, but under reasonable assumptions, the estimated treatment effect is conservative (biased upwards toward zero), as I demonstrate below.

In a two-period difference-in-differences model the causal effect of treatment in the treatment state, δ, is

$$\delta = \\ (E[Y_{st}|s = TREATMENT, t = 2] - E[Y_{st}|s = TREATMENT, t = 1]) - \\ (E[Y_{st}|s = CONTROL, t = 2] - E[Y_{st}|s = CONTROL, t = 1])$$

But because of the incomplete availability of pre-treatment data, I observe not $E[Y_{st}]$ but $E[Y_{st} + \mu_{st}]$. For ease of notation, let $\mu_2^{TREAT} = E[\mu_{st}|s = TREAT, t = 2]$. Thus rather than δ, the calculated difference-in-differences is actually

$$\tilde{\delta} = \delta + (\mu_2^{TREAT} - \mu_1^{TREAT}) - (\mu_2^{CONTROL} - \mu_1^{CONTROL})$$

I assume further that firms report all chemicals used when disclosure is mandatory; that is, $\mu_2^{TREAT} = 0$. Depending on the sign and relative magnitude of the μ values there are several scenarios under which $\tilde{\delta} \geq \delta$ and, therefore, a negative observed treatment effect ($\tilde{\delta}$) is conservative, and the true treatment effect δ is both negative, and larger in magnitude, than $\tilde{\delta}$. I provide theoretical and empirical support for one of these scenarios, specifically,

that in which both (i) ${\mu_1}^{TREAT} \leq 0$ and (ii) $(\mu_2^{CONTROL} - \mu_1^{CONTROL}) \leq 0$.[13]

Condition (i) simply states that a firm not subject to mandatory disclosure would, in expectation, disclose a subset of fractures (or a subset of chemicals per fracture) that is weakly cleaner than its full set. This is supported by theories of corporate environmental strategy (e.g., Lyon and Maxwell, 2004) which generally indicate that when firms have a choice about what kinds of activities to reveal publicly, they will choose to report those that appear more socially or environmentally responsive. Though it would usually be impossible to test this empircally in an analysis of disclosure, an unusual 14-month period in Pennsylvania provides a setting to do just that.

Pennsylvania's first disclosure law, effective in February 2011, required companies to report fracturing fluid contents to the state Department of Environmental Protection (DEP). The resulting reports were available for public inspection at regional DEP offices, where individuals wishing to access them had to identify the permit number of a specific well, contact the appropriate regional DEP office, file a request, schedule an appointment to visit in person (typically three to four weeks in advance), and review a limited number of hard copy documents onsite (typically up to 25 at a time).[14] Moreover, media coverage of the new regulation was minimal: to my knowledge only one general-audience news article, published nearly twelve months after the regulation effective date, mentions the 2011 law (Maykuth, 2012). Thus, while the 2011 Pennsylvania law technically constituted public disclosure, the main audience for the disclosures was the regulator, and in general operators would not have expected widespread public inspection of their fluid contents.

At the same time, many operators chose to report chemical additives to the national web-based registry FracFocus, where any individual with access to the internet could quickly download the same information provided they had the well location (e.g., state and county)

[13]This is obviously stronger than necessary to conclude $\tilde{\delta} \geq \delta$.

[14]Individuals could also access some of the information from the Integrated Records and Information System (IRIS), where some chemical disclosure forms were available as scanned PDF documents. IRIS contains substantial information on local geologic conditions and other items for each well, and most of its users are firms that pay a substantial subscription fee; however, any member of the public can also schedule an appointment at one of two Pennsylvania locations to use the system onsite for free. Even so, there was a long wait time for reports to be scanned and uploaded to IRIS, especially in the height of the fracturing boom (Pennsylvania Department of Conservation and Natural Resources, 2010). Using IRIS several times in 2011-2015, I found the upload delay was often on the order of 18 to 24 months, an observations that was confirmed by my conversations at the time with staff responsible for uploading reports.

or well identification number. Operators made this reporting decision on a well-by-well basis. Although an industry coalition encouraged its members to report to FracFocus starting in January 2012, reporting to FracFocus was entirely voluntary in Pennsylvania until April 2012. On April 14 of that year a new law took effect, requiring operators to disclose chemical information directly to FracFocus.

Using the inspection procedures described above, I obtained information on chemicals used in fracturing fluid for 344 unconventional wells in Pennsylvania for which operators revealed chemical additives only to regulators under the 2011 law. At the same time, operators posted to FracFocus information on chemicals for 1,527 wells in Pennsylvania fractured between the effective date of the first law (February 5, 2011) and the second (April 14, 2012). Table 7 compares values for the log concentration of PTRCs and log concentration of high-media-profile chemicals between the two sets of reports. For the first, the average reported quantity is significantly lower for public disclosures than for regulator-only disclosures; for the second there is no significant difference. Taken together, this test supports condition (i) above, i.e., that firms' voluntary disclosures are weakly cleaner than the full set.

[Table 7 about here.]

Condition (ii) states that on average, the degree of under-reporting does not diminish within an unregulated state after a regulation takes effect in an earlier-regulated state. I am not aware of a theoretical analysis that provides clear evidence in support of or against this proposition, but some empirical evidence can be extracted from the regulatory episode in Pennsylvania described above. Given that Pennsylvania acts as a control state for the early portion of my study period (because its public disclosure law takes effect sequentially fourth in my seven-state sample), measuring $(\mu_2^{CONTROL} - \mu_1^{CONTROL})$ amounts to evaluating the coefficient β_3 in the difference-in-differences style regression

$$Y_i = \beta_0 + \beta_1 POST_i + \beta_2 DEP_i + \beta_3 POST_i \times DEP_i + \epsilon_i \tag{4}$$

In which $POST_i$ is an indicator variable equal to one for well i fractured after disclosure is mandatory in an earlier-regulated state, and DEP_i is an indicator equal to one for well i whose chemical contents are disclosed only to the regulatory body.

Table 8 provides the results of this regression for wells in Pennsylvania fractured during the 14 months from February 2011 to April 2012.[15] The coefficient on the interaction term represents $\mu_2^{CONTROL} - \mu_1^{CONTROL}$ for this particular late-regulated state, Pennsylvania. While the results in Table 8 suggest that $\mu_2^{CONTROL} > \mu_1^{CONTROL}$, at least for the log concentration of PTRCs, the difference is not significantly different from zero, which supports the notion that operators did not significantly reduce the quantity of under-reporting of sensitive chemicals after disclosure regulations took effect in earlier states.

[Table 8 about here.]

Taken together, the theoretical and empirical evidence presented in this section suggests that the implication of incomplete voluntary reporting is that a negative estimate for δ from (1) or (2), or δ_τ from (3), is likely to be biased upward, toward zero, compared to the true effect of the regulation. Stated another way, the full-reporting effect is likely to be weakly positive, and the use of voluntarily reported data as the pre-treatment measure of toxic chemical use in fracturing fluid is likely to result in a lower-bound estimate of the effects of the disclosure regulations. In some cases, a lower bound estimate may not be interesting. As I show below, the estimated treatment effect in this setting is quite large, and so the fact that this is a lower-bound estimate makes my findings even more interesting.

5 Results

I report regression results separately for each dependent variable. In each set of results, I distinguish between the full set of fractures and fractures conducted by VR75 operators. By construction, the magnitude of the full-reporting effect is smaller for VR75 operators; thus, the results of analyses limited to the VR75 operators identify more clearly the disclosure-pressure effect.

[15] I define $POST_i = 1$ for wells fractured after February 1, 2012, which is the earliest regulation date in my seven-state sample.

5.1 Relative toxicity

Table 9 reports results from the estimation of models in which the dependent variable is the log of relative toxicity. Column 1 shows the results of estimating equation (1), regressing log relative toxicity on available well characteristics with fixed effects for state, year, geologic play, and operator. In this model the effect of disclosure laws is positive, though not significant. However, the observed effect is a composite of the full reporting effect (which is expected to be positive and large, as suggested by the analysis in Section 4.2.1) and the disclosure pressure effect. Column 4 shows the result for VR75 operators. The effect of mandatory disclosure for this subset of operators is still positive, but barely. This is consistent with the expectation that the full reporting effect is smaller in magnitude for operators who voluntarily report a large proportion of wells.

[Table 9 about here.]

Column 2 shows the results of estimating equation (2), which includes all of the variables from equation (1) but adds a state time trend and fixed effects for operator-by-year. The effect of mandatory disclosure in this model is still positive, and is larger in magnitude. Column 5 shows the same model for the subset of voluntary reporters; once again the effect of mandatory disclosure appears positive though not significant.

Column 3 of Table 9 shows the results of estimating equation (3), which is identical to equation (2) but demonstrates the effect of the disclosure regulation over time both before and after the effective date. This result is also shown visually in Figure 1. The corresponding results for VR75 operators are shown in column 6 of Table 9, and Figure 2. For both sets of operators, no distinct pre-trend appears for the difference between control and treatment, validating the parallel trends assumption. Figure 1 suggests the disclosure rule had no effect based on the composite effect of full reporting and disclosure pressure; however, Figure 2 and column 6 of Table 9, which isolate the disclosure-pressure effect more precisely, suggest the regulation had a negative effect on the relative toxicity of fracturing fluids. This effect is statistically significant ($p<0.05$) starting about three quarters after the regulation, is persistent over time, and amounts to a 37% to 59% reduction in relative toxicity, based on coefficient estimates ranging from -0.47 to -0.89.

[Figure 1 about here.]

[Figure 2 about here.]

5.2 Priority toxic and regulated chemicals

Table 10 shows the results for priority toxic and regulated chemicals, organized identically to those in the prior table. The results for all operators in columns (1) and (2) suggest that the combination of the full reporting effect and disclosure pressure effect is slightly negative, though not significantly different from zero. The results for VR75 operators in columns (4) and (5) are also negative, with the point estimate implying the disclosure regulation caused a reduction in the concentration of priority toxic and regulated chemicals of about 15-22%; however, this result is not statistically different from zero. Figures 3 and 4 show the results of the regulations over time. Both figures support the validity of the parallel pre-trend assumption. The results for all operators (Figure 3) show little change over time; the point estimate for the effect of the regulation is negative for most of the period after regulation, but generally not statistically significant. Focusing on VR75 operators, which more cleanly isolates the disclosure-pressure effect, the regulation appears to have had a consistently negative impact on the use of toxics over time, with significant effects starting nine months after mandatory disclosure. The coefficient ranges from -1.15 to -1.85 for the period from three to twelve quarters after regulation (Table 10, column 6), implying a persistent 68% to 84% decrease in PTRCs.

[Table 10 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

5.3 High-media-profile chemicals

Table 11 shows results for high-media-profile chemicals. Again, columns (1) and (2), with effects for all operators, provide suggestive evidence of increased use of these chemicals

(based on the composite of disclosure-pressure and full-reporting effects)—though the point estimates are not significantly different from zero. The same is true for VR75 firms, shown in columns (4) and (5).

Figures 5 and 6 show the effects of the disclosure laws over time. Firms' use of high-media-profile chemicals was decreasing for treatment states from about 18 to 12 months prior to the effective date of the disclosure laws, but was about the same for the year prior. This could reflect an attempt to deflect regulations by reducing the use of high-media-profile chemicals during a time of increased regulatory attention, although without further quantitative or qualitative evidence this is uncertain. Figure 6 suggests firms eventually decreased their use of high-profile chemicals, starting about 8 or 9 quarters after regulations, with decreases on the order of 45% to 76% (coefficient estimates from -0.59 to -1.44, per column (6) in Table 11).

[Table 11 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

These results are consistent with the idea that operators respond to disclosure laws by reducing use of toxics regardless of perceived (by media) potential harms. This is also in accord with the policies of at least one company (that shared with me a summary of their chemical use policy in the wake of disclosure laws), which require a tiered approval process for the use of toxic chemicals, with increasingly greater management approval required for chemicals of higher toxicity (but makes no mention of media coverage). To the extent that media focus has little to no correlation with actual toxicity, the apparent use of greater quantities of high-media-profile chemicals, if they substitute for more toxic chemicals, may be desirable from a public health and environmental standpoint. In addition, the observation that reductions in PTRCs occurred sooner, were more consistent over time, and were generally larger in magnitude also assuages a concern that might otherwise arise—that firms took advantage of disclosure policies that rely on self-reported data and misrepresented their use of toxic chemicals. If misreporting were widespread, we would expect reductions in observed use of high-profile chemicals that were at least as large, if not larger, than that of PTRCs.

5.4 Proprietary chemicals

Table 12 and Figures 7 and 8 show the impact of the disclosure regulations on concentration of chemicals declared as proprietary information. The pre-regulation trend evident in the two figures suggests the parallel trends assumption does not hold: that is, operators used higher concentrations of proprietary chemicals in treatment states, compared to control states, leading up to the passage of the mandatory disclosure regulation. Thus, while the concentration of proprietary chemicals increased in treatment states relative to control states after the mandatory disclosure regulations, it is not clear that this increase is caused by the regulations.

[Figure 7 about here.]

[Figure 8 about here.]

[Table 12 about here.]

Nevertheless, it is worth considering whether aspects of mandatory disclosure regulations would have inspired operators to increase their declaration of proprietary chemicals. When reporting is voluntary, some operators may choose not to list or not to quantify proprietary chemicals, instead listing only those chemicals whose identity is declared. Thus, the observed increase in the quantity of chemicals declared proprietary after disclosure laws may result from the fact that the disclosure laws formalized the necessity to report proprietary chemicals when they are used in fracturing fluid.

Other explanations may also be at work. One possibility is that operators were concerned about revealing trade secrets in the process of complying with disclosure laws, and used the proprietary declaration to avoid revealing strategically valuable information. Another possibility, considering the results from this section together with Sections 5.1 and 5.2, is that operators sought to avert public or stakeholder pressure by using the proprietary declaration to cover the ongoing use of toxic or regulated chemicals.

5.5 Robustness checks

One critical identifying assumption of the difference-in-differences approach is that in the absence of the regulatory treatment, the ex post trends in chemical use would have been parallel for states with and without the mandatory disclosure regulation. One way to verify the validity of this assumption is to implement a "placebo" regulation that occurs prior to the actual regulation, then run the same regressions as in the main specification and look for significant effects of the placebo regulation. If there are, then the main estimates could reflect some other process (e.g., a secular time trend) rather than a causal effect of the regulation.

To implement this check, I drop all treated observations (i.e., wells that were subject to mandatory disclosure) and then create a placebo policy variable that turns on one year before disclosure becomes mandatory in the corresponding state. I run a difference-in-differences analysis for each dependent variable, using the same specifications described above, to see if the analysis of the placebo policy suggests a significant change due to this (placebo) treatment. In each specification (including the time-varying approach as in (3)), the coefficient on the placebo treatment indicator is not statistically significant. This result increases my confidence in the validity of the main conclusion.

As a second robustness check, I consider the possibility that operators decreased the use of all chemical additives after the mandatory disclosure regulations. If this were the case, then this would provide an alternative explanation for the observed decrease in total concentration of toxic and regulated chemicals in fracturing fluid. To test this alternative explanation I run two additional specifications. First, I employ an alternative dependent variable equal to the total concentration of all chemicals (other than water and sand). Second, I choose a random subset of 45 chemicals (i.e., about the same number of elements as the subset of PTRCs) and calculate a dependent variable equal to the log of total concentration of that random set. In both cases, the analysis does not indicate the mandatory disclosure regulations had a significant effect.

Finally, I recalculate t-statistics for the main regressions using a wild cluster bootstrap. As noted in Section 4, hypothesis tests based on White (2000) cluster-robust standard errors tend to over-reject the null hypothesis. Several alternatives exist to correct for this (Cameron

et al., 2008; Cameron and Miller, 2015; Mackinnon and Webb, 2016; Webb, 2014). The results reported above reflect the correction that is most straightforward to implement, which is to use $G - 1$ degrees of freedom for t-tests. I also run an analysis using a wild cluster bootstrap with the six-point Webb distribution (Mackinnon and Webb, 2016; Webb, 2014) to recalculate p-values. The bootstrapped standard errors are somewhat greater than the errors using the $T(G - 1)$ distribution, but coefficients are still statistically significant in general; for instance, for the results corresponding to column 6 of Table 10 (that is, log PTRCs for voluntary reporters) the resulting p-values over the range from four to ten quarters after the regulation range from 0.068 to 0.086. This reinforces the validity of the main conclusion.

6 Conclusion and policy implications

Taken together, the difference-in-difference analysis and robustness checks suggest that mandatory disclosure of chemical additives in hydraulic fracturing fluids caused a decrease in both the overall concentration of toxic and regulated chemicals and the relative toxicity of chemicals used. The resulting decrease is not immediate, and its magnitude is difficult to quantify precisely, because the observed effect of switching from a voluntary to a mandatory reporting regime combines a "full reporting effect" and a "disclosure pressure effect." I show that the full reporting effect is large and positive, and that the disclosure pressure effect is large and negative—ranging from a 37% to 59% decrease in relative toxicity, and a 68% to 84% decrease in the use of priority toxic and regulated chemicals. Furthermore, this effect is persistent over time, lasting at least three years after disclosure regulations take effect. Firms also decrease the use of chemicals that are frequently mentioned by media as potentially dangerous or toxic, on the order of 45% to 76%; this effect is slower to manifest, a finding that supports the notion that firms are making real reductions in toxics use and not just gaming the system to avert media attention to their activities.

The results offer encouraging evidence for the hypothesis that mandatory information disclosure regulations can influence companies to change their behavior in ways that decrease potential threats to external stakeholders—in this case, harms to human health and

the environment that may arise from the use of toxic chemicals. Furthermore, the analysis demonstrates that even companies in non-consumer-facing settings—and where the disclosed information is presented in a highly technical format—may change their behavior in this way. This provides an important expansion of the findings from other domains where the information presented is more legible to consumers, and the regulated actors are more readily exposed to consumer pressure. Thus, the analysis provides useful insights for both policymakers and researchers regarding how firms respond to mandatory disclosure regulations in, potentially, a much larger set of contexts. These conclusions are also relevant for policymakers who must choose between alternative regulatory instruments, or specific design elements of instruments, for promoting public welfare.

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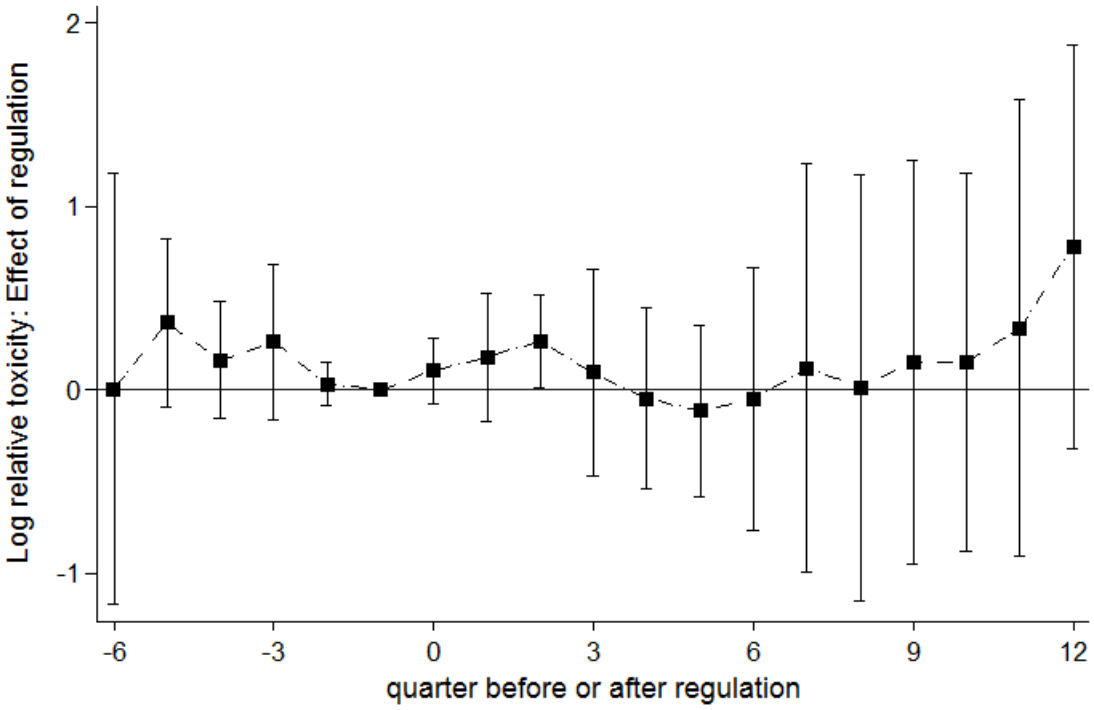
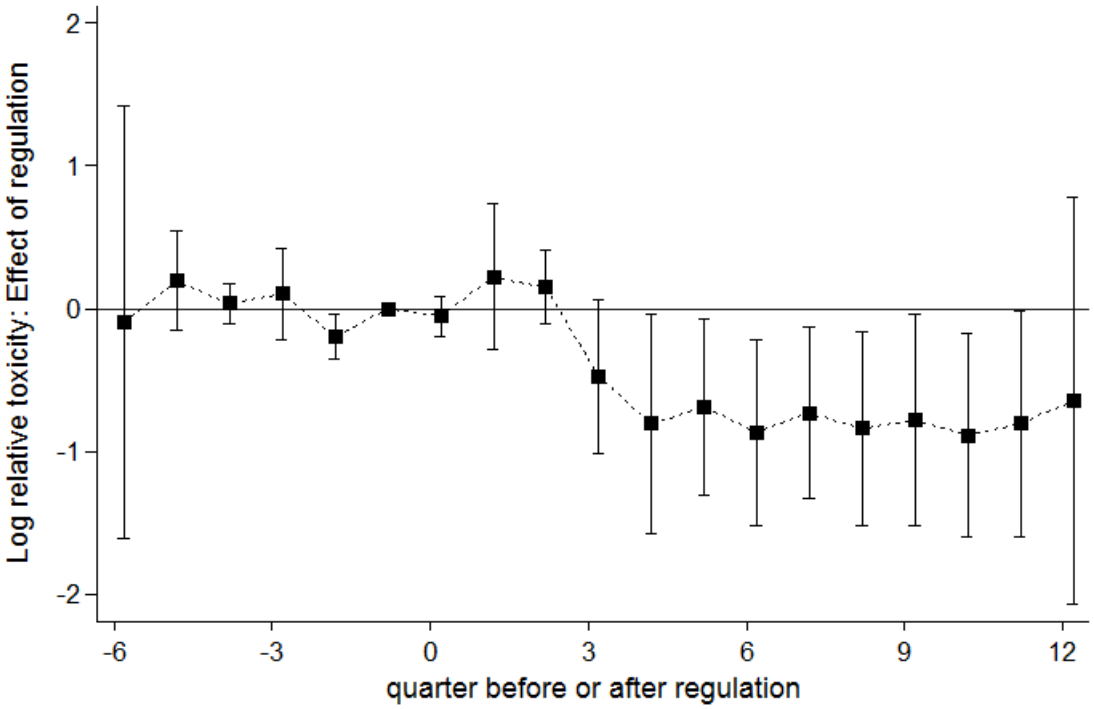
Figure 1: Difference in differences for log relative toxicity score, all operators



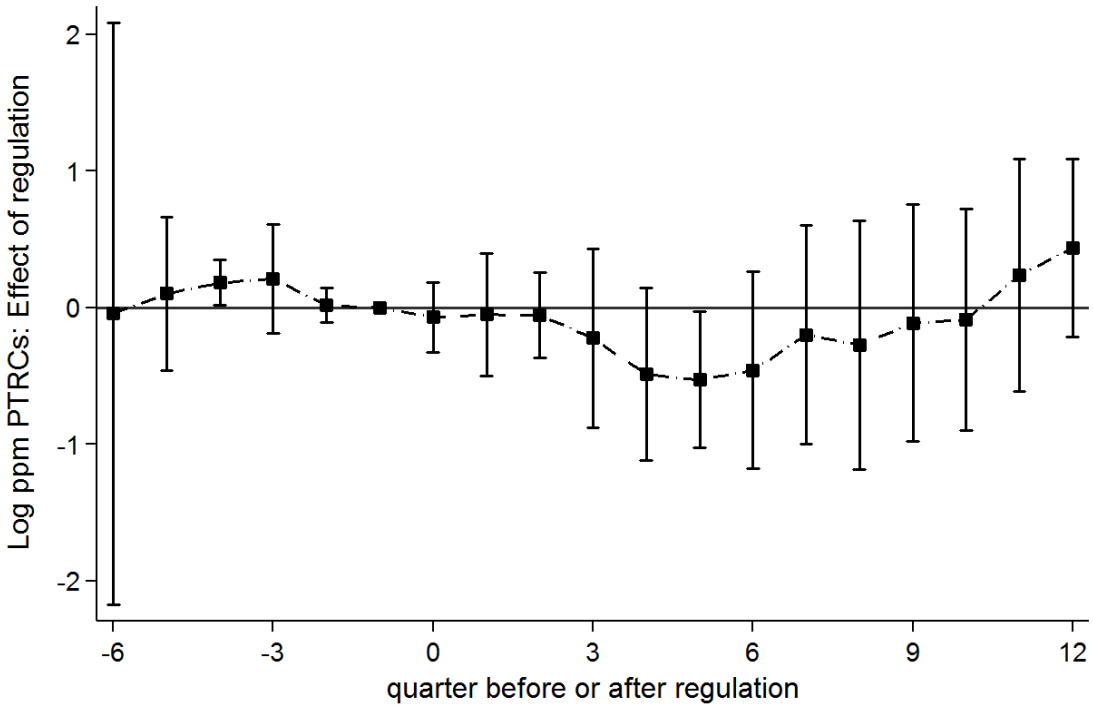
N=71,989 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 2: Difference in differences for log relative toxicity score, VR75 operators



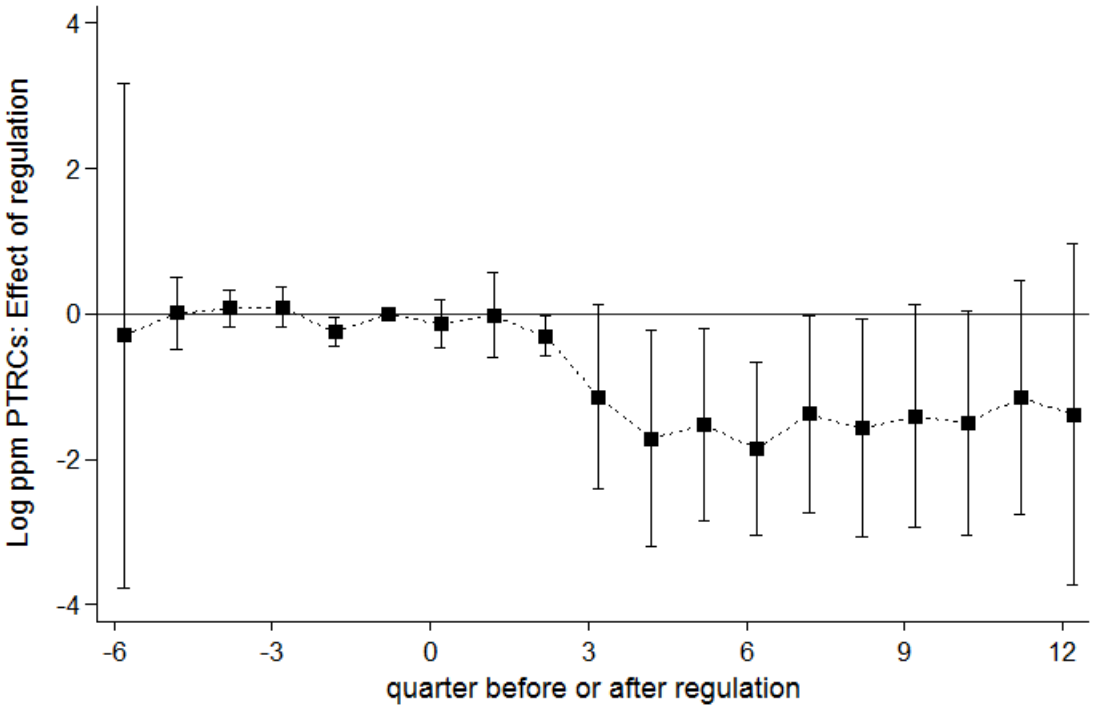
N=33,914 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 3: Difference in differences for log concentration PTRCs, all operators



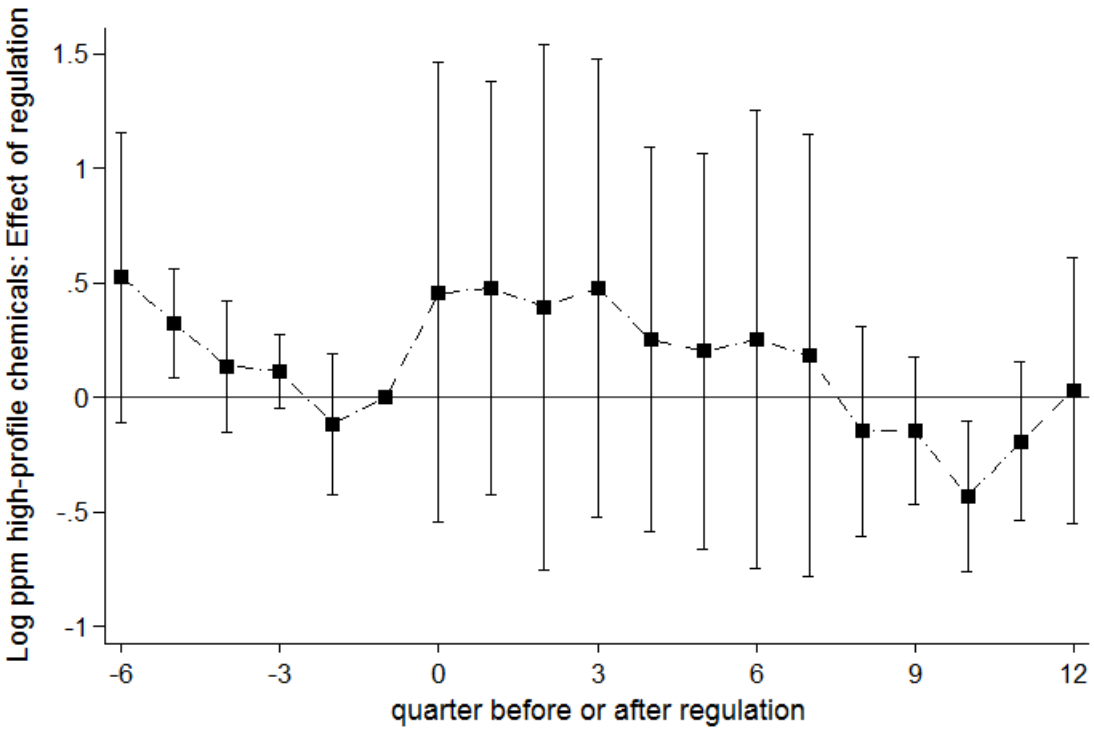
N=71,989 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 4: Difference in differences for log concentration PTRCs, VR75 operators



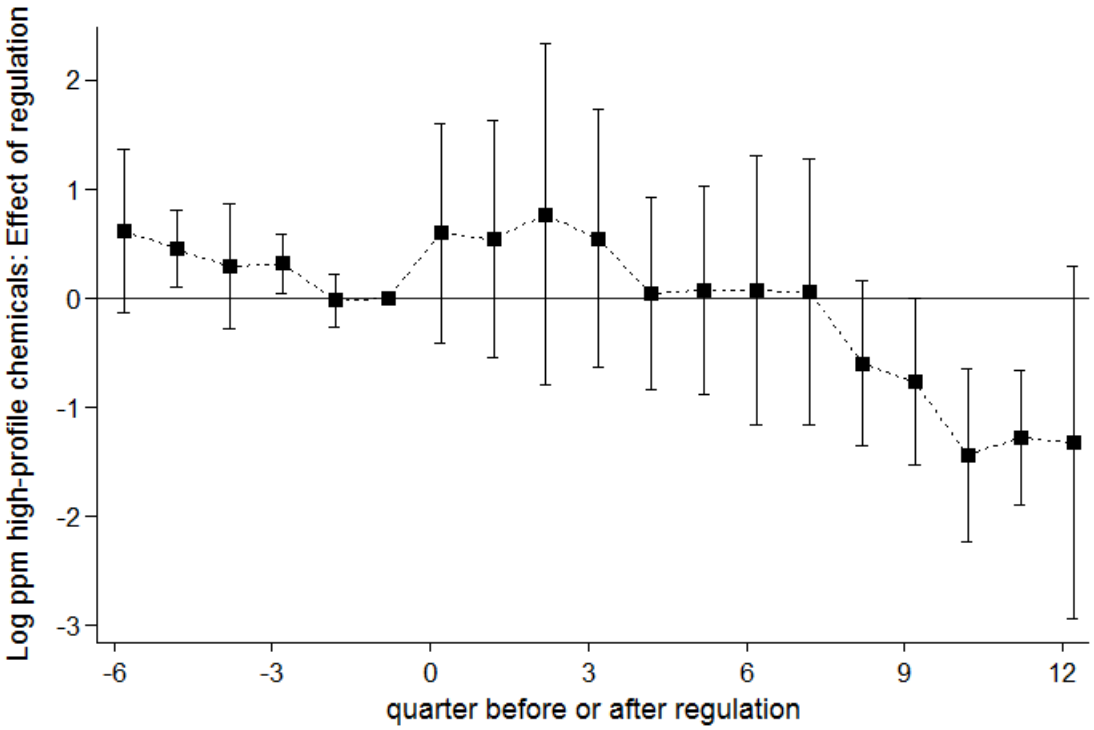
N=33,914 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 5: Difference in differences for log concentration high-media-profile chemicals, all operators



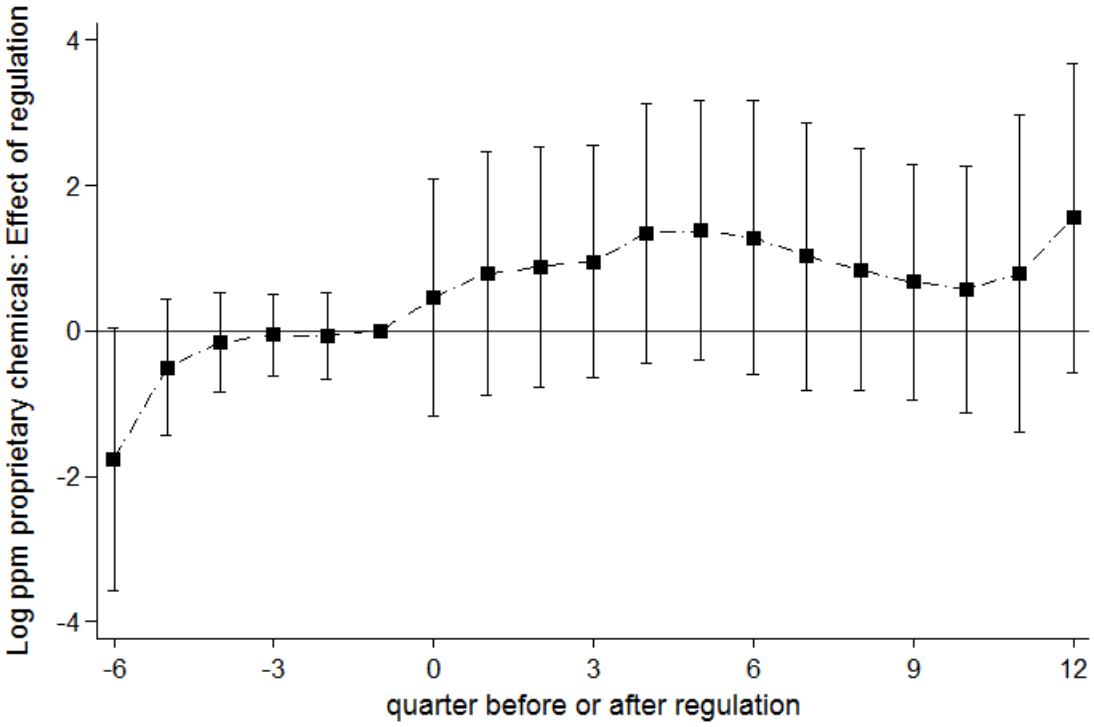
N=71,989 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 6: Difference in differences for log concentration high-media-profile chemicals, VR75 operators



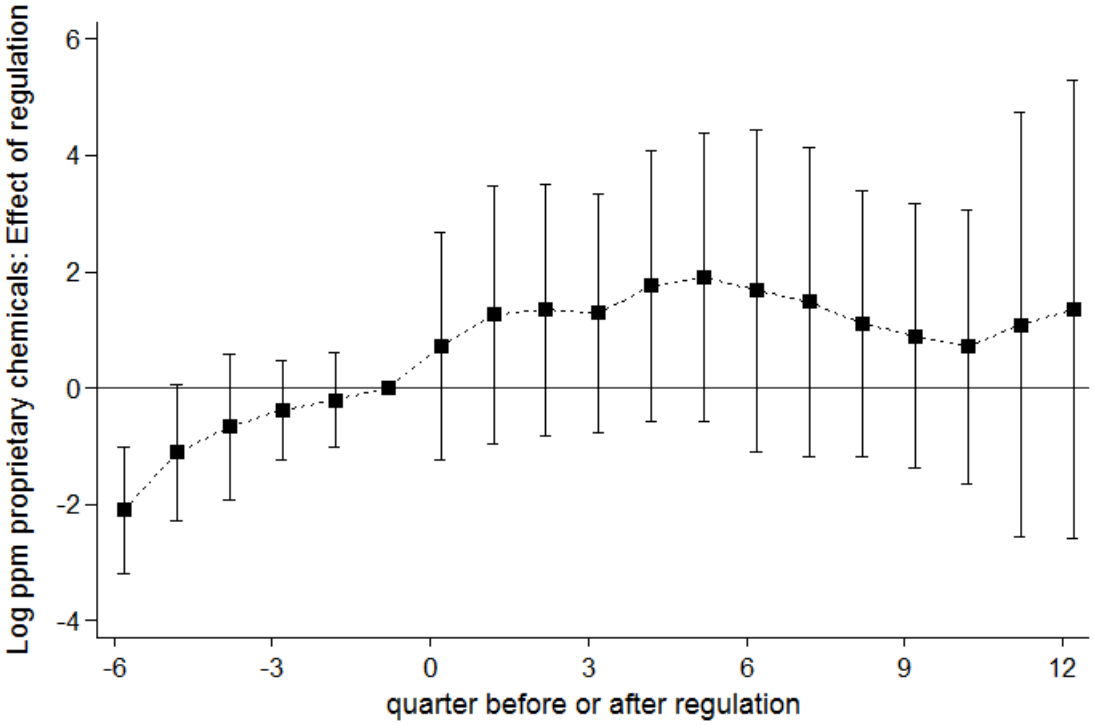
N=33,914 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 7: Difference in differences for log concentration proprietary chemicals, all operators



N=71,989 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Figure 8: Difference in differences for log concentration proprietary chemicals, VR75 operators



N=33,914 wells. Error bars show 95% confidence interval. Standard errors, clustered by state, use $T(G-1)$ critical values (Cameron and Miller, 2015).

Table 1: State disclosure laws

State	Regulation Effective date	Basis for effective date	Reporting location
Wyoming	5-Sep-10	Frac job	State agency
Arkansas	15-Jan-11	Drilling permit	State agency
Michigan	22-Jun-11	Frac job	State agency
Montana	27-Aug-11	Frac job	FracFocus or state agency
West Virginia	29-Aug-11	Frac job	State agency
Louisiana	20-Oct-11	Drilling permit	FracFocus or state agency
Texas	1-Feb-12	Drilling permit	FracFocus
New Mexico	15-Feb-12	Frac job	State agency
Colorado	1-Apr-12	Frac job	FracFocus
North Dakota	1-Apr-12	Frac job	FracFocus
Pennsylvania	16-Apr-12	Frac job	FracFocus
Ohio	11-Jun-12	Frac job	FracFocus or state agency
Utah	1-Nov-12	Frac job	FracFocus
Oklahoma	1-Jan-13	Frac job	FracFocus[1]
Mississippi	4-Mar-13	Frac job	FracFocus or state agency
Alabama	9-Sep-13	Frac job	FracFocus
Kansas	2-Dec-13	Frac job	FracFocus or state agency
California	1-Jan-14	Frac job	FracFocus or state[2]

Excludes some states with little or no fracturing activity.
1. Operators in Oklahoma may choose to report to the state, but by law the Oklahoma regulator reports to FracFocus any information it receives.
2. California changed the mandatory reporting location to the state agency as of January 2016.

Table 2: States, wells, and operators (all operators)

State	Effective date of disclosure regulation	Wells	Percent wells voluntarily reported	Number of operators
Texas	2/1/2012	40,569	23%	518
Colorado	4/1/2012	8,802	39%	95
North Dakota	4/1/2012	7,011	14%	53
Pennsylvania	4/16/2012	5,045	31%	45
Utah	11/1/2012	3,261	35%	32
Oklahoma	1/1/2013	6,513	25%	198
California	1/1/2014	2,010	54%	14
Total		73,211	26%	767

In Texas, disclosure is not required for wells with initial drilling permits prior to the effective regulation date, even if the fracturing job happens after that date.
Total number of operators is less than the sum of the column because some operators work in more than one state.

Table 3: States, wells, and operators (voluntary reporter [VR75] operators)

State	Wells	Percent wells fractured by VR75 operators	Number VR75 operators	Percent operators among VR75
Texas	18,301	45%	46	9%
Colorado	6,688	76%	14	15%
North Dakota	2,133	30%	8	15%
Pennsylvania	3,889	77%	22	49%
Utah	1,495	46%	6	19%
Oklahoma	1,860	29%	14	7%
California	16	1%	3	21%
Total	34,382	47%	58	8%

Total number of operators is less than the sum of the column because some operators work in more than one state.

Table 4: Voluntary reporter status of 25 largest operators

Operator	Wells	Operator % of wells	VR75	VR90
Anadarko	5,027	6.9%	yes	yes
Chesapeake Operating, Inc.	3,952	5.4%	yes	
EOG Resources, Inc.	3,405	4.7%	yes	
Pioneer Natural Resources	2,837	3.9%	yes	
Apache Corporation	2,416	3.3%	yes	
XTO Energy (ExxonMobil)	2,318	3.2%		
Devon Energy Production Co., LP	2,044	2.8%		
Sandridge Energy	2,029	2.8%		
Occidental Oil And Gas	1,959	2.7%		
Noble Energy Inc.	1,633	2.2%	yes	
Encana Oil & Gas (USA) Inc.	1,527	2.1%	yes	yes
Aera Energy LLC	1,472	2.0%		
WPX Energy	1,467	2.0%	yes	yes
ConocoPhillips	1,417	1.9%	yes	yes
Marathon Oil	1,348	1.8%	yes	yes
Newfield Exploration	1,304	1.8%		
Chevron USA Inc.	1,139	1.6%		
Energen Resources Corporation	1,123	1.5%		
Continental Resources, Inc.	1,074	1.5%		
Whiting Oil And Gas Corporation	1,051	1.4%		
BHP Billiton Petroleum	918	1.3%		
Hess Corporation	855	1.2%	yes	yes
Range Resources Corporation	750	1.0%	yes	
Laredo Petroleum, Inc.	710	1.0%		
COG Operating LLC	673	0.9%		
Total (top 25)	44,448	60.7%	yes (12)	yes (6)

Table 5: Descriptive statistics

Variable	N	Mean	SD	Minimum	Maximum
Well depth (ft)	73,211	8,507	2,925	100	25,000
Fluid volume (10^6 gal)	73,211	3,130	3,108	1	15,000
Oil well	73,211	0.61	0.49	0	1
Vertical wellbore	71,989	0.31	0.46	0	1
Log relative toxicity score	73,211	-0.4	2.89	-4.61	8.25
Log ppm PTRCs	73,211	-0.65	3.59	-4.61	12.43
Log ppm high-media-profile chemicals	73,211	2.7	3.74	-4.61	11.36
Log ppm proprietary chemicals	73,211	3.42	4.88	-4.61	14.24
Relative toxicity score	73,211	52	387	0	4,667
PTRC chemicals (ppm)	73,211	484	9,305	0	211,263
High-media-profile chemicals (ppm)	73,211	558	5,435	0	98,863
Proprietary chemicals (ppm)	73,211	3,028	43,412	0	4,750,000

Depth is winsorized at a lower bound of 100 feet and upper bound of 25,000 feet. Water volume is winsorized at a lower bound of 1,000 gallons and upper bound of 15,000,000 gallons.

Oil wells include wells that produce oil and gas together.

Log relative toxicity score, log ppm PTRCs, and log ppm high-media-profile chemicals are winsorized at the 75th percentile plus 1.5 times the IQR (for 490, 490, and 190 values, respectively). To accommodate zero values of the underlying levels, 0.01 (ppm) is added to the underlying level for all values. Varying the magnitude of this adjustment does not qualitatively change results.

Table 6: Comparison of means under voluntary and mandatory reporting regime

	All operators (N = 73,211 wells)		
	Voluntary Mean	Mandatory Mean	Difference Mean
Variable	(SE)	(SE)	(SE)
Well depth	0.837	0.856	0.0188***
(10^4 ft)	(0.002)	(0.0013)	(0.0024)
Water volume	2.407	3.386	−0.978***
(10^6 gal)	(0.0179)	(0.0140)	(0.0228)
Oil well	0.511	0.641	−0.130***
	(-0.004)	(0.002)	(0.004)
Vertical wellbore	0.341	0.306	0.035***
	(0.003)	(0.002)	(0.004)
Log relative	-0.560	-0.35	−0.21***
toxicity score	-0.02	-0.01	-0.02
Log ppm PTRCs	-0.77	-0.61	−0.17***
	-0.03	-0.02	-0.03
Log ppm high-media-	2.63	2.72	−0.09***
profile chemicals	-0.03	-0.02	-0.03
Log ppm proprietary	2.6	3.72	−1.12***
chemicals	(0.04)	(0.02)	(0.04)

All significance tests allow for unequal variances by group.
* p<0.10, ** p<0.05, *** p<0.01.
Well direction (e.g., vertical wellbore) is known for only 71,989 wells.

Table 7: Chemical use in FracFocus and DEP reports during "semi-public" disclosure

Measure	Public (FracFocus) mean (SE)	Regulator only mean (SE)	Difference in means (SE)
Log ppm PTRCs	-1.65 (0.07)	-1.09 (0.19)	-0.55*** (0.20)
Log ppm high-media-profile chemicals	1.02 (0.07)	1.01 (0.22)	-0.01 (0.23)

Includes 1,527 wells disclosed to FracFocus and 344 wells disclosed to PADEP between February 2011 and April 2012.
Significance test allows for unequal variances by group.
* p<0.10, ** p<0.05, *** p<0.01.

Table 8: Chemical use in regulator-only disclosures over time

	(1) Log ppm PTRCs	(2) Log ppm high-profile chemicals
Constant	-1.596***	1.032***
	(-20.15)	(11.29)
POST (mandatory disclosure in early-treated state)	-0.228	-0.0766
	(-1.34)	(-0.39)
DEP (Reported only to regulator)	-0.466	0.110
	(-0.24)	(0.05)
POST × DEP	1.201	-0.0598
	(0.62)	(-0.03)
R^2	0.0072	0.0001
N	1,871	1,871

Includes 1,527 wells disclosed to FracFocus and 344 wells disclosed to PADEP between February 2011 and April 2012.
* p<0.10, ** p<0.05, *** p<0.01.

Table 9: Regression results for log relative toxicity score

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
Depth (10^4 ft)	0.09	0.10	0.10	-0.14	-0.03	-0.04
	(0.25)	(0.21)	(0.21)	(0.34)	(0.46)	(0.45)
Fluid volume	-0.06**	-0.06***	-0.06***	-0.11**	-0.11***	-0.11***
(10^6 gal)	(0.02)	(0.01)	(0.01)	(0.04)	(0.02)	(0.02)
Oil well	0.29*	0.19*	0.21**	0.61	0.32**	0.33**
	(0.14)	(0.09)	(0.08)	(0.33)	(0.11)	(0.11)
Vertical	-0.09	-0.02	-0.02	-0.16	0.06	0.06
	(0.14)	(0.06)	(0.06)	(0.14)	(0.09)	(0.09)
Mandatory	0.09	0.16		0.02	0.08	
disclosure	(0.16)	(0.09)		(0.11)	(0.10)	
6 qtrs before reg.			0.01			-0.10
			(0.51)			(0.66)
5 qtrs before reg.			0.37			0.20
			(0.20)			(0.15)
4 qtrs before reg.			0.16			0.04
			(0.14)			(0.06)
3 qtrs before reg.			0.26			0.10
			(0.18)			(0.14)
2 qtrs before reg.			0.03			-0.20**
			(0.05)			(0.07)
0 qtrs after reg.			0.11			-0.05
			(0.08)			(0.06)
1 qtr after reg.			0.18			0.22
			(0.15)			(0.22)
2 qtrs after reg.			0.26*			0.15
			(0.11)			(0.11)
3 qtrs after reg.			0.10			-0.47*
			(0.25)			(0.23)
4 qtrs after reg.			-0.04			-0.81*
			(0.22)			(0.33)
5 qtrs after reg.			-0.11			-0.69**
			(0.21)			(0.27)
6 qtrs after reg.			-0.05			-0.87**
			(0.31)			(0.28)
7 qtrs after reg.			0.13			-0.73**
			(0.49)			(0.26)
8 qtrs after reg.			0.02			-0.84**
			(0.51)			(0.29)
9 qtrs after reg.			0.16			-0.78*
			(0.48)			(0.32)

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
10 qtrs after reg.			0.16			-0.89**
			(0.45)			(0.31)
11 qtrs after reg.			0.34			-0.81*
			(0.54)			(0.34)
12 qtrs after reg.			0.79			-0.64
			(0.48)			(0.62)
FEs: Oper., state, year, play	✓	✓	✓	✓	✓	✓
FEs: Play × year	✓	✓	✓	✓	✓	✓
FEs: Oper. × year		✓	✓		✓	✓
State-year trends		✓	✓		✓	✓
R^2	0.31	0.41	0.41	0.35	0.44	0.44
N	71,989	71,989	71,989	33,914	33,914	33,914

Standard errors are clustered by state, and adjusted for "few clusters" by using $T(G-1)$ critical values (Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01.

Table 10: Regression results for log ppm of PTRCs

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
Depth (10^4 ft)	0.70***	0.77***	0.78***	0.14	0.27	0.27
	(0.14)	(0.16)	(0.16)	(0.37)	(0.59)	(0.57)
Fluid volume	-0.03***	-0.04**	-0.04**	-0.08**	-0.09***	-0.09***
(10^6 gal)	(0.01)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)
Oil well	0.01	-0.09	-0.07	0.15	-0.11	-0.08
	(0.15)	(0.06)	(0.05)	(0.41)	(0.17)	(0.19)
Vertical	-0.00	0.04	0.04	-0.09	0.15	0.15
	(0.16)	(0.06)	(0.06)	(0.16)	(0.13)	(0.13)
Mandatory	-0.19	-0.07		-0.26	-0.16	
disclosure	(0.22)	(0.11)		(0.20)	(0.12)	
6 qtrs before reg.			-0.04			-0.30
			(0.92)			(1.50)
5 qtrs before reg.			0.10			0.01
			(0.24)			(0.22)
4 qtrs before reg.			0.18**			0.07
			(0.07)			(0.11)
3 qtrs before reg.			0.21			0.10
			(0.17)			(0.12)
2 qtrs before reg.			0.02			-0.25**
			(0.05)			(0.08)
0 qtrs after reg.			-0.06			-0.14
			(0.11)			(0.14)
1 qtr after reg.			-0.05			-0.02
			(0.19)			(0.25)
2 qtrs after reg.			-0.06			-0.31**
			(0.14)			(0.12)
3 qtrs after reg.			-0.21			-1.15*
			(0.28)			(0.55)
4 qtrs after reg.			-0.48			-1.72**
			(0.27)			(0.64)
5 qtrs after reg.			-0.52*			-1.53**
			(0.22)			(0.57)
6 qtrs after reg.			-0.45			-1.85**
			(0.31)			(0.52)
7 qtrs after reg.			-0.19			-1.38*
			(0.35)			(0.59)
8 qtrs after reg.			-0.26			-1.58*
			(0.40)			(0.65)
9 qtrs after reg.			-0.10			-1.41*
			(0.38)			(0.66)

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
10 qtrs after reg.			-0.08			-1.50*
			(0.35)			(0.67)
11 qtrs after reg.			0.24			-1.15
			(0.37)			(0.70)
12 qtrs after reg.			0.44			-1.38
			(0.28)			(1.02)
FEs: Oper., state, year, play	✓	✓	✓	✓	✓	✓
FEs: Play × year	✓	✓	✓	✓	✓	✓
FEs: Oper. × year		✓	✓		✓	✓
State-year trends		✓	✓		✓	✓
R^2	0.30	0.38	0.38	0.29	0.36	0.37
N	71,989	71,989	71,989	33,914	33,914	33,914

Standard errors are clustered by state, and adjusted for "few clusters" by using $T(G-1)$ critical values (Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01.

Table 11: Regression results for log ppm high-media-profile chemicals

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
Depth (10^4 ft)	-0.50	-0.50*	-0.50*	-0.07	0.03	-0.01
	(0.27)	(0.25)	(0.25)	(0.63)	(0.42)	(0.44)
Fluid volume	-0.07***	-0.07***	-0.06***	-0.09**	-0.09**	-0.08**
(10^6 gal)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Oil well	0.29**	0.19	0.17	0.46**	0.26	0.23
	(0.12)	(0.17)	(0.17)	(0.14)	(0.22)	(0.20)
Vertical	-0.00	0.07	0.07	-0.32***	-0.15	-0.13
	(0.12)	(0.07)	(0.07)	(0.06)	(0.12)	(0.13)
Mandatory	0.36	0.47		0.50	0.62	
disclosure	(0.37)	(0.43)		(0.47)	(0.49)	
6 qtrs before reg.			0.53			0.62
			(0.27)			(0.32)
5 qtrs before reg.			0.33**			0.45**
			(0.10)			(0.15)
4 qtrs before reg.			0.14			0.29
			(0.12)			(0.25)
3 qtrs before reg.			0.11			0.32**
			(0.07)			(0.12)
2 qtrs before reg.			-0.11			-0.02
			(0.13)			(0.11)
0 qtrs after reg.			0.46			0.60
			(0.44)			(0.44)
1 qtr after reg.			0.48			0.54
			(0.39)			(0.47)
2 qtrs after reg.			0.39			0.77
			(0.50)			(0.68)
3 qtrs after reg.			0.49			0.55
			(0.44)			(0.51)
4 qtrs after reg.			0.26			0.04
			(0.37)			(0.38)
5 qtrs after reg.			0.21			0.08
			(0.38)			(0.42)
6 qtrs after reg.			0.26			0.07
			(0.44)			(0.54)
7 qtrs after reg.			0.19			0.06
			(0.42)			(0.53)
8 qtrs after reg.			-0.13			-0.59
			(0.20)			(0.33)
9 qtrs after reg.			-0.13			-0.77*
			(0.14)			(0.33)

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
10 qtrs after reg.			-0.42**			-1.44***
			(0.14)			(0.34)
11 qtrs after reg.			-0.19			-1.27***
			(0.15)			(0.27)
12 qtrs after reg.			0.03			-1.32
			(0.25)			(0.70)
FEs: Oper., state, year, play	✓	✓	✓	✓	✓	✓
FEs: Play × year	✓	✓	✓	✓	✓	✓
FEs: Oper. × year		✓	✓		✓	✓
State-year trends		✓	✓		✓	✓
R^2	0.36	0.44	0.44	0.33	0.38	0.39
N	71,989	71,989	71,989	33,914	33,914	33,914

Standard errors are clustered by state, and adjusted for "few clusters" by using $T(G-1)$ critical values (Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01.

Table 12: Regression results for log ppm proprietary chemicals

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
Depth (10^4 ft)	-0.12	-0.05	-0.07	-0.18	0.08	0.07
	(0.53)	(0.56)	(0.56)	(0.58)	(0.62)	(0.62)
Fluid volume (10^6 gal)	-0.03	-0.02	-0.02	-0.09	-0.08	-0.08
	(0.04)	(0.03)	(0.03)	(0.05)	(0.04)	(0.04)
Oil well	0.00	0.20	0.16	0.21	0.48*	0.46
	(0.17)	(0.12)	(0.12)	(0.49)	(0.24)	(0.24)
Vertical	-0.01	-0.13	-0.12	0.07	-0.08	-0.03
	(0.19)	(0.26)	(0.25)	(0.36)	(0.38)	(0.36)
Mandatory disclosure	0.69	0.65		1.04	1.05	
	(0.60)	(0.69)		(0.81)	(0.87)	
6 qtrs before reg.			-1.76*			-2.10***
			(0.79)			(0.47)
5 qtrs before reg.			-0.51			-1.11*
			(0.40)			(0.50)
4 qtrs before reg.			-0.16			-0.67
			(0.30)			(0.54)
3 qtrs before reg.			-0.05			-0.38
			(0.24)			(0.37)
2 qtrs before reg.			-0.08			-0.21
			(0.26)			(0.35)
0 qtrs after reg.			0.46			0.73
			(0.71)			(0.85)
1 qtr after reg.			0.79			1.26
			(0.72)			(0.96)
2 qtrs after reg.			0.88			1.35
			(0.72)			(0.94)
3 qtrs after reg.			0.95			1.28
			(0.69)			(0.89)
4 qtrs after reg.			1.34			1.75
			(0.78)			(1.01)
5 qtrs after reg.			1.38			1.91
			(0.77)			(1.08)
6 qtrs after reg.			1.28			1.68
			(0.82)			(1.20)
7 qtrs after reg.			1.03			1.48
			(0.80)			(1.15)
8 qtrs after reg.			0.84			1.11
			(0.72)			(0.99)
9 qtrs after reg.			0.67			0.90
			(0.70)			(0.98)

	All operators			VR75 operators		
	(1)	(2)	(3)	(4)	(5)	(6)
10 qtrs after reg.			0.57			0.72
			(0.74)			(1.02)
11 qtrs after reg.			0.79			1.09
			(0.94)			(1.58)
12 qtrs after reg.			1.55			1.35
			(0.93)			(1.71)
FEs: Oper., state, year, play	✓	✓	✓	✓	✓	✓
FEs: Play × year	✓	✓	✓	✓	✓	✓
FEs: Operator × year		✓	✓		✓	✓
State-year trends		✓	✓		✓	✓
R^2	0.36	0.46	0.46	0.30	0.40	0.40
N	71,989	71,989	71,989	33,914	33,914	33,914

Standard errors are clustered by state, and adjusted for "few clusters" by using $T(G-1)$ critical values (Cameron and Miller, 2015).
* p<0.10, ** p<0.05, *** p<0.01.