Mandatory Environmental Disclosure and Pollution Avoidance Behavior*

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ABSTRACT

We study whether mandating corporate environmental disclosure prompts the general public to adopt pollution avoidance behavior. Our setting is the disclosure policy change in the US fracking industry, where the use of chemicals poses risks to water quality but has long been concealed from the public. Following firms' chemical disclosure, we observe an 8.5 percent increase in defensive spending—measured by bottled water sales—in fracking counties compared to control counties with oil and gas activities but no fracking. The avoidance behavior is more pronounced in states where chemical information receives greater media coverage and is easier for residents to acquire and integrate. Moreover, the public spends more on bottled water when operators report a larger number of toxic or trade secret chemicals, suggesting that heightened perceived risk drives avoidance behavior. We also document significant heterogeneity in public response across various household and demographic characteristics. Finally, we provide suggestive evidence of health benefits associated with avoidance behavior. Overall, our findings highlight an important channel through which mandating corporate environmental disclosure can reduce public pollution exposure.

Keywords: mandatory environmental disclosure; information-based regulation; real effects; pollution information; consumer behavior; pollution avoidance behavior; fracking

JEL Classification: D10; H31; I12; K32; L71; L72; M41; M48; Q58

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1. INTRODUCTION

Information-based regulations serve as the cornerstone of modern pollution control strategies because they have significantly reduced the resources required for regulatory enforcement (Tietenberg, 1998).[1] Estimating the full benefits of information regulations is crucial for assessing the effectiveness of disclosure-based regulatory approaches. This requires a comprehensive understanding of their impact on both polluters (disclosing entities) and victims (the public exposed to pollution). Prior literature primarily focuses on disclosing entities and shows that disclosing environmental information can reduce public pollution exposure by encouraging improved operational practices, much like traditional compliance tools. While disclosure regulations do not directly restrict emissions, increased transparency motivates polluters to *reduce* pollution through public shaming and peer benchmarking (Bonetti et al., 2024; Christensen et al., 2021; Tomar, 2023; Yang et al., 2021). In this paper, we shift the focus from polluters to victims, investigating whether corporate environmental disclosure prompts the general public to mitigate exposure by actively *avoiding* pollution.[2]

Our focus on the victims' pollution avoidance behavior is grounded in the premise that polluters often fail to fully internalize the negative externalities they generate. It remains unclear whether transparency-driven environmental efforts by polluters can sufficiently offset the adverse impacts on exposed populations. A more plausible scenario is that industrial pollution is likely to persist at significant levels even after disclosure mandates. Therefore, it is crucial to examine whether corporate transparency influences the behavioral responses of "affected individuals", as their avoidance actions may play a pivotal role in mitigating

[1] Traditional compliance-based regulations, such as command-and-control regulations (e.g., explicit emission standards) or market-based mechanisms (e.g., cap-and-trade systems, emissions tax), can be excessively burdensome for regulators to design, implement, monitor, and enforce effectively in certain circumstances (Karkkainen, 2001).

[2] Our study focuses on the behavior of *the general public*–individuals who are (potentially) affected by operators' polluting actions (e.g., residents) but typically do not have direct economic ties to them (e.g., consumers, shareholders, or suppliers).

pollution-related health risks. If this is the case, our current assessments of the benefits of corporate environmental disclosure are likely *understated*. Indeed, a considerable portion of the societal benefits from reduced pollution exposure could arise from the public's adaptive behavior rather than changes in the operational practices of disclosing entities.

It is not a priori obvious whether mandating corporate environmental disclosure prompts the general public to engage in pollution avoidance behavior. On the one hand, disclosing corporate environmental information can alter the public's perceptions of pollution exposure. Prior to these mandates, the public may have held vague expectations about pollution levels, remaining largely uncertain about the specific pollutants and their quantities. Releasing environmental data reduces this uncertainty, potentially prompting behavioral changes as individuals become more confident in their assessments (Ilut and Schneider, 2022). Moreover, environmental disclosure often triggers cascading changes, such as expanded access to environmental data, increased media coverage of pollution issues, and heightened awareness of the negative consequences of previously hidden pollutants (Barwick et al., 2023). The elevated salience of environmental information may greatly enhance the public's awareness of pollution issues and drive stronger avoidance behavior.

On the other hand, simply providing corporate environmental information may not be sufficient to prompt public action, particularly if the information is difficult to process (Blankespoor et al., 2020). The concept of avoidance behavior emerges from the environmental economics literature, which collectively suggests that disseminating risk alerts enables the public to engage in behavioral responses that minimize associated risks (Bresnahan et al., 1997; Janke, 2014; Liu et al., 2018; Zivin et al., 2011; Zivin and Neidell, 2009). However, the information examined in these studies primarily consists of salient alerts issued by the local government, such as tap water violation notices and wildfire smoke alerts. Several features make it challenging to directly apply these findings to corporate disclosures. First, unlike risk alerts, where regulators disseminate risk information directly to affected individuals, corporate environmental disclosures do not target a clearly defined audience. Second, risk alerts emphasize health risks explicitly, whereas corporate disclosures typically present *factual* environmental information (e.g., the identities and quantities of chemicals) that lacks explicit warnings about possible health risks associated with pollutants. Third, risk alerts often include additional guidance on recommended actions (e.g., boiling water, staying indoors), while corporate disclosures do not provide instructions on how to mitigate pollution risks. This lack of contextualization in corporate environmental information can create barriers, such as information integration costs, that limit the public's ability to effectively use corporate disclosures (Blankespoor et al., 2020).

Furthermore, mandatory environmental disclosure exposes operators' pollution activities to public scrutiny, facilitating peer benchmarking and exerting public pressure on operators (Christensen et al., 2021). The pressure can arise from various sources, including both product and capital markets (consumers and investors favoring environmentally responsible firms), the labor market (greener firms being better able to attract and retain moral employees), the judicial system (victims seeking compensatory damages), or the legislature (policymakers advocating for stricter regulations) (Tietenberg, 1998). Consequently, firms may alter their practices to reduce pollution due to reputational concerns (e.g., Bonetti et al., 2024). If the public anticipates these pollution-reducing effects, they may revise their perceived pollution risk downward and feel less compelled to take further costly avoidance actions to mitigate health risks. In sum, mandating firms to disclose environmental information may or may not change the public's perceptions and behaviors. It remains an open question whether and how the public responds to corporate environmental disclosures.

Our research setting is the hydraulic fracking (HF) industry in the United States. HF is an unconventional oil and gas extraction technology that enables operators to drill oil and gas from reserves previously considered non-producible. The rise of HF has significantly boosted US oil and gas production, making the country a global leader in energy production. However, the fracking process involves the injection of large volumes of fracking fluids underground (Trickey et al., 2020), raising public health concerns such as drinking water safety. The composition of fluids used to be highly opaque within the industry. To reduce public anxiety, most fracking states in the US have introduced mandatory chemical disclosure programs, requiring oil and gas operators to publicly disclose the detailed chemical composition of fracking fluids.[3]

Since drinking water safety is a key public health concern regarding the use of fracking chemicals, we follow prior economics literature and use bottled water sales from NielsenIQ's Retail Scanner to construct the proxy for avoidance behavior (Allaire et al., 2019; Wrenn et al., 2016; Zivin et al., 2011). Our sample comprises a comprehensive county-week-level sales dataset spanning from 2006 to 2019. The staggered rollout of chemical disclosure programs across states allows us to implement a Difference-in-Differences (DID) framework. Specifically, we compare changes in bottled water sales before and after the first fracking disclosure event between counties with fracking activities (treatment group) and conventional oil and gas counties without fracking activities (control group). We include county fixed effects to control for time-invariant factors that affect local consumer demand, and year-week fixed effects to account for temporal and seasonal sales trends.

Our empirical findings suggest that the public engages in more pronounced avoidance behavior after fracking operators start disclosing chemical information. Following the fracking

[3] It is noteworthy that uncertainties still exist regarding the actual impact of fracking chemicals on drinking water safety and human health. The industry generally claims that fracking is safe and has a minimal impact on the environment. The US Environmental Protection Agency (EPA) has completed a six-year scientific assessment of the effects of fracking on drinking water resources. Although the EPA concludes that fracking can impact water resources under certain conditions, it still highlights the lack of studies and calls for more research on this issue (EPA, 2015). Having said that, we expect human beings to be more conservative on health-related issues and to still take necessary precautions in the face of uncertainties when presented with environmental information.

disclosure, fracking counties experienced an approximately 8.5 percent increase in bottled water sales compared with non-fracking oil and gas counties. These findings highlight an important implication of mandating environmental disclosure in fracking: in the absence of binding regulations on chemical use, corporate disclosure can prompt the public to take defensive actions to mitigate perceived health risks.[4]

Building on our baseline results, we next examine the key information-related mechanisms through which fracking disclosure affects avoidance behavior: awareness, acquisition, and integration costs that can impede individuals from effectively utilizing corporate disclosures (Blankespoor et al., 2020). While most fracking states mandate chemical disclosure via FracFocus–a user-friendly, publicly accessible national registry, others allow direct reporting to regulators in arguably less accessible formats, with voluntary reporting on FracFocus. This flexible reporting structure may also introduce self-selection bias. We find that bottled water sales increase significantly only when FracFocus reporting is mandatory. Moreover, upgrades to FracFocus that improve data accessibility are linked to stronger avoidance behavior, highlighting the importance of easy access to information.

Since the public may not be aware of such information or may not have the capacity to extract useful signals from the raw data, we next assess the role of media in alleviating information barriers. We find that avoidance behavior is more pronounced in states with heightened media coverage of fracking activities and associated health risks. Results on Google search trends further confirm the role of information awareness and integration in driving behavioral changes.

Finally, we examine whether avoidance behavior is driven by heightened perceptions of pollution exposure resulting from chemical disclosures. Geographical variations in chemical

[4] Although water pollutants are regulated by the Clean Water Act in the US, the fracking industry has received many federal exemptions and is only subject to the regulation in several specific situations (e.g., when diesel fuel is used in operations).

usage reveal stronger avoidance behavior in counties where operators disclose a larger number of toxic or trade-secret chemicals, suggesting that public avoidance is shaped by perceived health risks following disclosure.

In additional analyses, we investigate how avoidance behavior varies by household and demographic characteristics. We find that the observed behavioral change stems from counties that did not frequently receive tap water violation notices in the pre-disclosure period, and is stronger in areas with higher exposure to fracking. Demographically, avoidance is more pronounced among low-income households and at-risk populations. We also find stronger responses in counties with a higher proportion of extraction industry workers, likely due to greater awareness of fracking-specific information.

Finally, we assess whether the documented avoidance behavior leads to improved health outcomes. Focusing on infant birth weight, a known indicator negatively affected by fracking (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022), we find that fracking disclosures are associated with overall improvements in infant health. The better health outcome can likely be attributed to the *combined* effect of pollution reduction (Bonetti et al., 2024) and pollution avoidance. Notably, the health improvement is greater in fracking counties with larger post-disclosure increases in bottled water sales, suggesting that avoidance behavior contributes meaningfully to better health outcomes.

Our paper contributes to the growing literature on the real effects of information-based regulations. Prior research (Bonetti et al., 2024; Dranove and Jin, 2010; Weil et al., 2006) shows that disclosure can lead firms to reduce pollution, often driven by public pressure and peer benchmarking (Christensen et al., 2021), suggesting that disclosure can incentivize firms to internalize their negative externalities. However, most studies focus on the behavior of disclosing entities (the polluters). We complement this work by shifting the lens to the public (the victims) and examining their behavioral response to corporate disclosures. Our findings suggest that information-based regulations can yield broader societal benefits beyond firm-level pollution reduction: increased environmental transparency prompts the public's pollution avoidance, leading to improved social outcomes. Moreover, this perspective underscores a key advantage of information-based regulations over traditional compliance-based regulatory approaches.[5] The latter, despite being binding and outcome-focused, may still leave the public exposed to hidden pollution due to enforcement failures, non-scientific standards, or insufficient internalization of externalities. In contrast, information-based regulations have the potential to empower individuals to act on disclosed information, offering a more participatory mechanism to mitigate health risk exposures.

This paper also relates closely to studies on avoidance behavior in environmental economics. Prior research (Barwick et al., 2023; Neidell, 2009; Zivin et al., 2011; Zivin and Neidell, 2009) primarily focuses on whether individuals engage in avoidance behavior in response to salient *risk alerts* issued by regulators, such as water quality violation notices (Allaire et al., 2019; Zivin et al., 2011), smoke alerts (Zivin and Neidell, 2009), and air pollution warnings (Barwick et al., 2023; Janke, 2014). The key difference between our study and prior literature is the distinct nature of corporate information provided to the public. Unlike regulatory warnings, corporate environmental disclosures present factual data (as opposed to directly revealing hazard risks)[6] and do not offer guidance on recommended actions to mitigate risk exposure.

[5] Traditional compliance-based regulations include command-and-control approaches, which impose specific performance or design standards, and market-based mechanisms such as taxes, subsidies or tradable permits. Command-and-control regulations often regulate only a limited set of pollutants due to resource constraints (e.g., only six regulated pollutants under the Clean Air Act). These standards must vary by pollutant and industry to balance economic and technological feasibility. Market-based mechanisms avoid this complexity but require regulators to set an overall pollution cap in advance, which can be difficult to estimate accurately.

[6] There is often no clear link between disclosed chemical information and its associated health risks. As Bae et al. (2010) argue, raw pollution information may be insufficient to convey health implications unless users can interpret and contextualize it. This challenge parallels findings in financial disclosure research, where individual investors struggle to analyze complex data due to high processing costs (Blankespoor et al., 2020).

Finally, our work adds to the nascent literature on ESG disclosures and consumer behavior (Beyer et al., 2023; Leonelli et al., 2023). Prior studies examine how firms' environmental disclosure shapes consumers' preferences for their own products, thereby incentivizing firms to internalize the negative externalities of their operations. In contrast, our study focuses on how corporate environmental disclosure influences the consumption behavior among broadly "affected individuals". While their consumption choices may help mitigate exposure to environmental risks, they do not directly pressure firms to internalize externalities. In this respect, our work aligns with Sinha (2022), who studies the impact of fracking disclosure on housing and lending markets.

2. FRACKING, DRINKING WATER SAFETY, AND DISCLOSURE

2.1 Hydraulic Fracking and Drinking Water Safety

In recent decades, technological advancements in HF have significantly lowered the cost of extracting energy resources from unconventional fields. In a conventional oil or gas field, where hydrocarbons are stored in relatively porous and permeable rock, oil and gas can flow naturally from the reservoir to the wellbore. However, a significant amount of oil and gas in the US is embedded in low-permeable rock formations such as shale.[7] Fracking enables extraction firms to recover oil and gas from rocks that were previously considered unworkable. The US Energy Information Administration (EIA) estimates that two-thirds of natural gas and crude oil production in the US relies on fracking technology (EIA, 2023). Despite its important role in the energy sector, fracking is associated with air pollution, water pollution, and earthquakes (Barth-Naftilan et al., 2018; Darrah et al., 2014; Osborn et al., 2011; Sherwood et al., 2016). These costs are generally borne by nearby residents who are exposed to fracking operations.

[7] A shale play is a group of oil fields in the same region that have a similar set of geological conditions.

Water pollution is a key environmental concern in fracking operations. The average fracking job injects approximately 5 million gallons of fluid into shale beds to force open rocks and extract hydrocarbons. While water and sand constitute 99 percent of fracking fluid, the remaining 1 percent contains thousands of chemicals classified as known or possible human carcinogens (Trickey et al., 2020). There are multiple channels through which fracking can impact water resources. Fracking has the potential to cause groundwater contamination in all stages of operations (Shrestha et al., 2017; Sun et al., 2019; Torres et al., 2016). The primary pathways are spills during chemical mixing and on-site treatment and waste management, well casing failures, induced fractures, tank leaks, and pipeline leaks (Hill and Ma, 2022). Beyond groundwater contamination, recent studies also provide large-sample evidence of the impact of fracking on surface water quality (Bonetti et al., 2021). Furthermore, wastewater is frequently sent to treatment plants that were not designed to treat it (GWPC, 2009). Concerns over water quality impacts have led the US EPA to investigate the impact of fracking on drinking water resources. The EPA concludes that, under certain conditions, fracking activities can lead to detrimental impacts on water resources (EPA, 2015). Overall, this literature suggests that systematic water contamination might exist in neighborhoods with extensive fracking operations.

However, it remains difficult for scientists to assess whether human beings are actually affected by water pollution from fracking. One possible approach is to examine the quality of water wells directly, but this method has multiple challenges (Hill and Ma, 2022). Since there are no regulatory requirements for sampling private water sources, it is difficult to capture water quality for them. Data on public water primarily focuses on the violations of regulated chemicals. Given the wide range of chemicals used in fracking, it is likely that regulators may have overlooked some non-regulated chemicals. Another approach is to assess the health outcomes of exposed populations. A critical hurdle here is the challenge of distinguishing the effects of water pollution from other factors that are correlated with proximity to fracking activities. Evidence in support of a water contamination pathway is thus incomplete (Currie et al., 2017; Hill, 2018). Hill and Ma (2022) have made some progress and used granular water source location data to isolate the effects of water pollution from fracking activities. Research in this area also predominantly focuses on infant health, not adults (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022). This leaves the exposed public uncertain about the extent to which they are affected by the fracking chemicals.

2.2 Fracking Disclosure Regulations

In the US, fracking is exempted from the Safe Drinking Water Act (SDWA) provision in most situations (unless diesel fuel is used). For decades, the industry has kept silent about the chemicals being used. Given the rising concern about the health implications of fracking chemicals, state governments have begun regulating fracking disclosure within state borders. In 2010, Wyoming became the first state to require oil and gas operators to disclose the identities of chemicals used in fracking operations. Currently, disclosure of chemical use in HF has been made mandatory in almost all states with extensive fracking activities.[8]

Most states require operators to publicly disclose the use of chemicals on FracFocus (the national HF chemical registry). A few other states allow a choice of submission between FracFocus or the state agency. FracFocus provides detailed information about each fracked well, including the fracking date, operator identity, well location, chemical identity, and chemical concentration level. Appendix C includes an example disclosure form. Operators are required to disclose the details of the fracking job between 30 and 120 calendar days after the spudding or well completion. While the default requirement is for operators to provide detailed information for each of the chemicals (including the Chemical Abstracts Service or CAS

[8] Appendix B summarizes the entry-into-force dates for different states.

number) used in their operations, the identity of chemicals claimed as trade secrets can be withheld from disclosure.

The fracking disclosure mandate has significantly reduced the information asymmetry between operators and the public. Since water pollution is not observable, external parties had a limited understanding of the use of chemicals in fracking prior to the disclosure mandate (Sinha, 2022). The disclosure program has facilitated local communities, media, and environmental Non-Governmental Organizations (NGOs) in monitoring the use of chemicals.[9] In addition, scientists have developed third-party searching apps based on the FracFocus data to further facilitate residents searching for well information near their homes.[10] In sum, operators' chemical information has been accessed by many parties for multiple purposes. Without information disclosure, the public would generally be left uninformed about their potential chemical exposure.

2.3 Bottled Water Purchase as an Averting Action

Bottled water purchase is a commonly recommended averting action often mentioned in public notifications. The quality standards for bottled water sold in interstate commerce are overseen by the Food and Drug Administration (FDA). The FDA regulations generally align with the quality standards set by the EPA for public water supplies. However, due to the absence of a current public database on the quality of bottled water, our understanding of bottled water quality is limited. In addition, bottled water produced and sold within a single state falls outside FDA regulation, though state health agencies may establish their standards. FDA also relies on sampling results from bottlers, rather than third-party laboratories. Therefore, we do not assume that bottled water is necessarily of higher quality than public tap water.

[9] In the Online Appendix A, we provide anecdotal evidence illustrating the attention from local media regarding the use of HF chemicals in local counties after the firms start disclosing fracking information.
[10] E.g., Well Explorer is a well searching app developed by researchers at the School of Medicine, the University of Pennsylvania. All chemical data are extracted from the FracFocus website. App users can enter the Zip code of their home address and search for chemical information of wells near their homes.

Nevertheless, bottled water is considered an economically viable alternative water source during violation periods. Several studies find that households consume more bottled water when regulators issue public notices of water violations (Allaire et al., 2019; Zivin et al., 2011). Similar evidence has also been documented when households perceive higher risks in water use but without receiving formal notices. Using water consumption data in the pre-disclosure period, Wrenn et al. (2016) find that households residing in shale-active counties in Pennsylvania spend more on bottled water compared with those living in similar counties without shale activity.[11] These results are consistent with households using bottled water to mitigate their perceived risks associated with fracking. Nevertheless, the public may have underestimated pollution exposure in the pre-disclosure period due to the lack of information on operating practices.

Ideally, the avoidance behavior would include all defensive measures that households take to avert risks from water pollution, such as purchasing bottled water, installing water filtration systems, and using on-site water tanks etc. In this paper, we focus solely on bottled water purchases due to data availability. Therefore, a caveat is that our estimate only provides a lower-bound estimation of avoidance behavior. It is also possible that households may take more extreme averting actions, such as migrating to cleaner areas. Nevertheless, the environmental justice literature generally supports the notion that households with disproportionate pollution exposures may face financial constraints and have limited choices in selecting residential areas (Banzhaf et al., 2019). Furthermore, the industry has generated numerous job opportunities in local areas since the early 2000s fracking boom (Wilson, 2022). Households also face a trade-off between favorable labor market conditions and exposure to

[11] Although both Wrenn et al. (2016) and our paper examine water consumption behavior in fracking counties, there are key differences between the two studies. Wrenn et al. (2016) primarily investigate public reactions to potentially polluting activities, whereas our focus is on examining the impact of information disclosure. Additionally, our DID approach allows us to isolate the incremental effect of information disclosure on top of the influence of polluting activities themselves.

pollution. In this regard, purchasing bottled water is a feasible way for them to mitigate potential health risks at a relatively lower cost.

3. DATA AND VARIABLES

3.1 Key Variables

Our data on the consumption of bottled water is derived from weekly sales (Sunday to Saturday) recorded in the NielsenIQ Retail Scanner dataset, covering weeks from January 1, 2006, to December 31, 2019. The NielsenIQ dataset encompasses various retail outlets, including grocery stores, drugstores, convenience stores, and mass merchandisers. NielsenIQ estimates that these stores account for over half of the total sales volumes in U.S. grocery and drug stores, as well as more than 30 percent of mass merchandiser sales volume. Our compiled dataset includes sales in dollars for over 70,000 Universal Product Codes (UPC) representing bottled water from more than 6,000 brands. This includes both flavored and unflavored water, along with different container sizes of the same product. Since the NielsenIQ dataset does not consistently provide information on the volume of water sold, we define our dependent variable (*Ln_watersales*) as the logarithm of aggregate sales in dollars (in 2019 dollars) for all UPCs by county and week.[12] To ensure that the change in sales data is not affected by the closure or opening of stores, we only keep stores that consistently report sales data in all weeks during our sample period. Figure 1a illustrates county-week-level average bottled water sales (log-transformed) during 2006-2019 (in 2019 dollars).

We obtain the chemical reporting data on HF wells from FracFocus and the location and time of wells drilled in the pre-disclosure period from Well Database (a commercial oil and

[12] We choose the county as the unit of analysis because the public's concern about water quality primarily stems from their local community water system. Allaire et al. (2019) analyze counties served by community water systems and show that the vast majority of these systems serve a single county (only 0.5% of water systems serve multiple counties). Our findings are robust to alternative definitions of treatment counties, such as those within the 5km county border or sharing the same watershed.

gas data vendor). We define fracking counties as those that both report HF wells and have oil and gas activities in the pre-disclosure period.[13] Our control group consists of counties that drill oil and gas wells in the pre- and post-disclosure periods but do not report HF wells in FracFocus. We define the DID estimator, *Disclosure*, to be one for all weeks following the first fracking disclosure event in each fracking county, and zero otherwise. Figure 1b illustrates the treatment and control counties on the map.

3.2 Control Variables

We control for a wide range of factors including tap water violation records, demographic characteristics, and weather conditions. Data on violations are extracted from the EPA Safe Drinking Water Information Systems (SDWIS) for the years 2006 to 2019. These data provide information on the contaminant(s) triggering the violation, the violation's start and end dates, and the county served by the community water system (CWS). If a violation occurs at a specific CWS, we classify the county served by that CWS as having a violation. Nearly all water systems serve only a single county, with only about 0.5% serving multiple counties (Allaire et al., 2019). Following Allaire et al. (2019), we construct two violation variables. Tier 1 violations (*Tier1_violation*) cover contaminants with an immediate health risk, such as pathogens and nitrate. Tier 2 violations (*Tier2_violation*) arise when water systems fail to comply with other requirements, such as MCL rules (Maximum Contaminant Level). We label the week of a county as under violation if a public notice is in effect.

We obtain the demographic data from the American Community Survey (ACS), which is available through the IPUMS National Historical Geographic Information System (NHGIS).

[13] Out of the 318 counties that report HF wells, only 11 did not have any oil and gas activities in the pre-disclosure period. These counties are likely new fracking towns. Including them in the treatment group may overestimate the treatment effect. Therefore, we drop these counties from the full sample. The results are largely similar if we keep these observations. Several states have passed the disclosure mandate but do not have fracking counties in our treatment sample either because no HF wells have been drilled (i.e., Idaho, North Carolina, South Dakota, and Tennessee) or due to the lack of continuous bottled water sales data in fracking counties (i.e., Alaska, Illinois, Indiana, Michigan, North Dakota, Nebraska, and Nevada).

Since the one-year estimates only cover counties with a population size of over 65,000, we follow the ACS handbook and use the five-year estimates, which have the largest sample size and highest precision. We use the end year of the five-year period to match with the year in our dataset (e.g., use the 2015-19 estimate to construct the census variables in 2019).[14] Our county-level census characteristics include median household income (*Ln_income*) and population (*Ln_population*). Since the relationship between population and bottled water sales is hump-shaped, we also control for the second order of the population variable (*Ln_population_sq*).[15]

Finally, since weather conditions might affect local water consumption demand (Allaire et al., 2019), we also construct weather variables during our sample period. We use the fine-gridded PRISM weather data from Wolfram Schlenker's website. The website publishes daily minimum and maximum temperatures, as well as total precipitation on a 2.5×2.5-mile grid for the contiguous United States. We calculate the average temperature (*Temperature*) and precipitation (*Precipitation*) for each week in each county.

Our main model includes county fixed effects to control for time-invariant factors that affect demand across different counties, such as personal preferences and differences in public notice among county health departments (Allaire et al., 2019). Since there is strong seasonality in bottled water sales, we also include year-week fixed effects to capture temporal and seasonal sales trends. The full definitions of the variables are available in Appendix A.

3.3 Descriptive Statistics

Our final dataset comprises 466,053 county-week level observations with non-missing variables for the years 2006 to 2019. Table 1 Panel A presents the summary statistics for the

[14] For 2006, 2007, and 2008, we use the 2005-2009 estimates because the multiyear data are not available before 2009. Since county-level population data is not available at the year level, we do not scale the sales variable by population in the main analyses. In Section 4.3, we find robust results when we use sales per capita as the dependent variable.

[15] As the population grows, there might be an increased demand for bottled water due to higher consumer density. However, in highly dense areas, the demand for bottled water may start to decrease as the market becomes saturated.

full sample. We winsorize the sales variable at the 99th percentile to limit the influence of outliers due to recording errors. In Panel B, we report the summary statistics by fracking (treatment) and control counties. Overall, fracking counties experience approximately 3 percent more water quality violations (both Tier 1 and Tier 2) than control counties.

Figure 2a illustrates the trend in bottled water sales for fracking and control counties at the year-week level. We observe strong seasonality in bottled water sales, with peak seasons occurring in the summer months.[16] These trends highlight the importance of including the year-week fixed effects in the model. In Figure 2b, we average the weekly sales data to the year level to illustrate the year trends in bottled water sales for fracking and control counties. The sales trends in fracking and control counties largely parallel during the sample period, while the sales in fracking counties seem to increase at a faster rate after 2010. This is consistent with the timeline of introducing mandatory disclosure rules in different fracking states.

4. MAIN RESULTS

4.1 Evidence of Avoidance Behavior

Our primary research question is whether the mandate requiring corporate disclosure of fracking chemical information affects public pollution avoidance behavior. To address this question, we estimate the following equation, leveraging variation in the timing of fracking disclosure implementation across counties:

$$Ln\_watersales_{c,w} = \beta \cdot Disclosure + \gamma' X_{c,w} + County_c + Year\text{-}week_w + \varepsilon_{c,w} \quad (1)$$

where $Ln\_watersales_{c,w}$ is bottled water sales (log-transformed) in week w in county c. The key variable of interest is the DID estimator, $Disclosure$. For the treatment counties $Disclosure$ equals 1 for the weeks after the first fracking disclosure made by firms, and 0 for

[16] In Figure 2a, we also observe seemingly outlier recordings for two weeks in our dataset (01-Jan-2011 and 31-Dec-2011, with a total of 1,276 observations). This is potentially due to the time error for these two weeks in the original dataset. Since these two weeks only represent 0.27 percent of the total observation, we do not drop them in our analyses. Our main results remain robust if we exclude these two weeks.

the weeks before. For the control counties, $Disclosure$ is always 0. Thus, the coefficient on $Disclosure$ (β) captures the difference in the changes in bottled water consumption before and after the fracking disclosures between the treatment and control counties. We expect β to be positive if there is an increase in bottled water sales from the pre- to post-disclosure period in fracking counties compared with that in conventional oil and gas counties. The control variables mentioned earlier are denoted by $X_{c,w}$. $County_c$ and $Year\text{-}week_w$ are county fixed effects and year-week fixed effects, respectively. Standard errors are clustered at the state level.

Table 2 presents the main results of estimating equation (1). Overall, we document a significant increase in bottled water sales for the treatment counties from the pre- to post-disclosure period compared with that in the control counties. Column (2) suggests that the economic magnitude of this behavioral change is approximately 8.5 percent and is deemed meaningful.[17] In sum, these findings suggest that the disclosure programs have nudged the general public to engage in pollution avoidance behavior. These results also imply that the public might have underestimated their pollution exposure prior to the introduction of disclosure mandates.

4.2 Parallel Assumption

A critical assumption for a DID design is the presence of common pre-trends in bottled water sales prior to the disclosure. To verify this assumption, we re-estimate equation (1) by replacing $Disclosure$ with time indicators for years relative to the first fracking disclosure event in each fracking county. For instance, *Year -1* and *Year 5* are two binary variables representing weeks within one year prior to the first fracking disclosure event and 5 years and beyond after the first fracking disclosure event in the focal fracking county, respectively. *Year*

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[17] Equation (1) implies that $\ln(1+y_{post}) = \ln(1+y_{pre}) + \beta$, where y_{pre} and y_{post} denote the bottled water sales before and after the first fracking disclosure event, respectively. Thus, the relative increase of bottled water sales is $\frac{y_{post}}{y_{pre}} - 1 = \left(1 + \frac{1}{y_{pre}}\right)e^{\beta} - \frac{1}{y_{pre}} - 1$. We set y_{pre} to the sample median of bottled water sales (71,051.527), this gives us a relative increase of 8.5 percent when β is 0.082. We calculate the economic magnitude in a similar way for the subsequent tests.

-1 serves as our benchmark and is omitted in the model. Figure 3 depicts the dynamic effects for the model shown in column (2) of Table 2, along with the respective 90 percent confidence intervals. The coefficients on the DID indicators are insignificant in all pre-disclosure periods. We find significant treatment effects in all post-periods, suggesting that the effect of disclosure on bottled water consumption is stable and constant. Overall, we do not find evidence suggesting that the parallel trend assumption is violated.[18]

4.3 Robustness Checks

We conduct a battery of tests to gauge the robustness of our main results. Given the variation in treatment timings across different states, our staggered DID model with two-way fixed effects structures may produce biased estimates (Baker et al., 2022; Goodman-Bacon, 2021). To address this concern, in Table 3 panel A columns (1)-(2), we adopt the stacked regression approach proposed by Cengiz et al. (2019) and find that our main inferences in Table 2 columns (1)-(2) remain unchanged.

Next, we employ the entropy balancing technique to address issues related to functional form misspecification (Hainmueller and Xu, 2013). We balance the mean, variance, and skewness of control variables across treatment and control counties to ensure that the distribution of observed covariates is similar across groups (untabulated). Table 3 panel A columns (3)-(4) report the main results after balancing. The results are generally consistent with those in Table 2, suggesting that the treatment estimates in our main model are not likely to suffer from bias due to potential differences in the characteristics of fracking and non-fracking counties.

[18] The selection of fracking chemicals depends on geological conditions while drilling the well, which varies by shale play and over time as the shale play resources are accessed (King and Durham, 2017). Most shale plays are located within a single state. For shale plays that span across two neighboring states, the adoption dates are very close to each other (e.g., Texas and New Mexico). Therefore, we do not expect strong spillover effects from early adopting states to late adopting states.

We also examine the robustness of the results to alternative approaches for defining the treatment counties. First, we assume the neighboring control county is also a treatment county if there is at least one HF well drilled within 5 km of the county borderline. Since pollutants might travel within the river system, we also assign a control county as a treatment county if it is located within the same watershed (HUC 10) as an HF county. Table 3 panel A columns (5)-(8) present the findings. We find robust results using these alternative approaches to defining the treatment group.[19]

In panel B, we assess the robustness of our results to alternative bottled water sales measures. We first scale the total sales by the five-year estimates of population and obtain similar results in columns (1)-(2). Given that the rise in bottled water sales could be influenced by both sales volume and unit price, we also analyze which factor primarily drives our findings. We collect non-missing volume information for bottled water sales and standardize the measurements to milliliters (ml). Next, we calculate the total volume of bottled water sold across all UPCs by county and week. We also obtain unit price data and calculate the average price of bottled water for all UPCs by county and week. Columns (3)-(6) report the results for sales volume and unit price. We find that the primary driver of the increase in bottled water sales is sales volume rather than unit price. Finally, we explore the change in consumption of other types of beverage goods. We replace bottled water sales with the sales of juice, milk, coffee, and liquor, which are less likely to be affected by chemical disclosure. We do not find fracking disclosure to have significant effects on the consumption of these beverages.

[19] In untabulated analyses, we also explore whether there is spillover effect of avoidance behavior to these "seemingly affected" neighbor control counties. We rerun equation (1) by comparing the bottled water consumption between these "seemingly affected" neighbor counties and other control counties. We do not find evidence suggesting any spillover effect. We suspect that this might be due to the lower exposure to fracking activities in these "seemingly affected" neighbor control counties. The median number of HF wells in our treatment sample is 70. This number is 4 for neighbor control counties that have HF wells within 5 km of the county border and 16 for neighbor control counties located within the same watersheds as treatment counties. These null results also imply that the public response is primarily based on the county information provided in the disclosure form.

In Online Appendix B.1, we examine the robustness of our results to different data processes. Our main dataset only retains stores that consistently report sales data in all weeks during the sample period. We relax this requirement and keep stores that report more than 90 percent and 80 percent of the weeks in our study period. This includes fracking counties in North Dakota in the treatment sample. All results remain robust. We rerun the results for unflavored bottled water only and find similar results. We also assess the robustness of the main results by considering alternative fixed effects structures. In our main model, the county fixed effects structure is the finest and should have controlled for most time-invariant characteristics at the local level. We find robust results if we further include state by year-month (year-week) fixed effects to control for state-specific trends surrounding the first fracking disclosure event. Finally, the results are robust if we expand the control group and include non-oil and gas counties.

5. MECHANISMS: INFORMATION FRICTIONS AND RISK PERCEPTION

Our baseline results suggest that the fracking disclosure has encouraged the general public to engage in more pronounced avoidance behavior. However, regulations do not come out of a vacuum. A potential threat to our analysis is that the main results may be confounded by other concurrent events, such as local policy debates surrounding the adoption of disclosure rules, which may also affect public awareness and avoidance behavior. While we cannot fully rule out such possibilities, we mitigate these concerns by highlighting two *information-related* mechanisms that shape pollution avoidance behavior: (1) reduced information frictions and (2) heightened perceptions of health risks stemming from the chemical disclosures. If the observed increase in bottled water sales were solely driven by confounding factors (rather than by the fracking disclosure), we would not expect to see differential effects across levels of information frictions.

5.1 Information Frictions: Acquisition Cost

States have significant discretion over the implementation details of regulations within their borders. We first exploit the variations in the default disclosure platform required by different state regulators. FracFocus is the official chemical disclosure platform in most large fracking states. This site was created to provide the general public with free access to information about chemicals and is user-friendly for consumers wishing to explore the data. Some other states have alternative arrangements, allowing operators to choose between filing with FracFocus or state regulators. State governments have their own information systems that maintain the operating and production records of oil firms. Acquiring data from state regulators is much more difficult because the well completion reports might not be machine-readable and are often more technical. Although reporting to FracFocus is generally encouraged by regulators, such filing flexibility introduces self-selection biases for the chemical information disclosed on FracFocus in those states.[20] Appendix B summarizes the default disclosure platform in each fracking state.

We split the treatment sample into two subgroups based on whether disclosure to FracFocus is mandatory or not. We then rerun equation (1) by replacing the DID estimator with two non-overlapping variables marking observations in the post-disclosure period in the respective subgroup. The results are reported in column (1) of Table 4. We only find a significant increase in bottled water sales in states where reporting to FracFocus is mandatory. Overall, these results suggest that whether information is required to be disclosed on an easy-to-access platform has some influence on avoidance behavior.

We also notice that FracFocus has undergone several important upgrades since its launch in 2011.[21] These upgrades allow users to search for and acquire well site chemical

[20] The average number of disclosed toxic chemicals is 110 per county for states with a default requirement of disclosing on FracFocus and 55 per county for states with alternative arrangements.
[21] There are three major upgrades during our sample period: 1) June 2013: FracFocus 2.0 is released, allowing users to efficiently search for well site chemical information. The new and improved XML platform provides options for searching and pulling reports by date ranges, chemical names, or CAS numbers, with additional enhancements in data validation. 2) July 2015: In response to public demand, FracFocus begins releasing

information more efficiently, significantly reducing information acquisition costs for the public. To measure these improvements, we construct a time-varying variable, $FFscore$, and add one to it for the periods after FracFocus underwent a major upgrade. We then interact this variable with the DID estimator to examine whether these site upgrades further facilitate behavioral changes. In Table 4 column (2), the coefficient on the triple interaction term is positive and highly significant. This result suggests that these site upgrades have further improved public transparency, making information access easier and more efficient.

5.2 Information Frictions: Awareness and Integration Costs

News media are the primary avenue that influences the public's awareness of new information. Since the general public may not have the capacity to analyze and extract useful signals from the raw data, the media also play a crucial role in facilitating information integration for the public. This is because media articles often summarise and highlight the key findings to the audience, such as whether toxic chemicals are found in operations in local areas. Online Appendix A provides two sample news articles. Besides, media coverage also leads to more information searches, which reflects an increase in information awareness. Bonetti et al. (2024) document consistent and robust evidence that media coverage and information search significantly increase after the disclosure mandates. In this section, we build on their existing results and examine the role of information awareness and integration in nudging avoidance behavior.

In the spirit of Bonetti et al. (2024), we obtain media articles containing the keywords "fracking" and terms related to health or pollution[22] in headlines from LexisNexis between 2006 and 2019. Next, we assign these articles to different fracking states based on the location

disclosure data to the public in SQL format, making it easier for users and researchers to search and aggregate data. 3) June 2016: FracFocus 3.0 goes live, introducing stronger validation processes to enhance data integrity. The update includes newly designed forms to improve the user experience for companies and regulatory agencies checking and completing disclosures.

[22] The terms we search include "pollution", "health", "water", "contaminant", and their variants.

of publication and count the number of articles in the pre- and post-disclosure periods in each state. Following Bonetti et al. (2024), we focus on the change in media exposure and calculate the difference in the number of articles in the pre- and post-disclosure periods. We partition the fracking states into high and low groups based on the quartile value of the change and keep the top and bottom quartiles. We then replace the DID estimator with two non-overlapping variables marking observations in the post-disclosure period in the respective group.[23]

Table 5 column (1) presents our findings. The coefficient on the estimator is positive and significant for the high group and insignificant for the low group. Therefore, avoidance behavior is only observed in states that have a significant increase in media exposure in the post-disclosure period. Regarding the low group, the change in the number of media articles is actually negative or near zero. These findings collectively underscore the importance of media in triggering public behavioral changes.

Next, we explore whether information search influences public responses. We follow Bonetti et al. (2024) and use the Google search trend for the term "fracking" to measure information search in different states. Similar to the analysis of media exposure, we calculate the change in the state-specific average Google search trend between the pre- and post-disclosure periods and split the fracking states into high and low groups based on the quartile value of the change. The middle two quartiles are dropped from the analysis.

Table 5 column (2) reports the results. Similar to our findings on media coverage, the increase in bottled water sales is only significant for the high group but is insignificant for the low group. Thus, we only observe strong avoidance behavior in states where there is an increased search for fracking-related information. These findings are largely in line with the

[23] We also assess the robustness of all other cross-sectional findings using alternative splits based on tercile and quintile values. The results largely remain robust (untabulated for brevity).

results for media exposure because the public's information search behavior is likely to be triggered by reading news.

5.3 Change in Risk Perception

A key argument of our study is that fracking disclosure elevates the public's risk perception, thereby nudging behavioral responses. To examine this mechanism more directly, we analyze the chemical information disclosed by operators and assess the public's response to two categories of chemicals that have the potential to alter risk perception: toxic chemicals and trade secret chemicals. This analysis provides more direct evidence that the behavioral change is shaped by the specific content of the information disclosed by operators.

Intuitively, the perceived health risk is expected to be higher if operators use more toxic chemicals in operations. We first examine whether the avoidance behavior is stronger in counties where operators report a larger number of toxic chemicals. We consider a chemical toxic if it has been reported as a commonly used toxic chemical by the US House of Representatives Committee on Energy and Commerce.[24] All of these chemicals have high media exposure and are reported as hazardous to human health (e.g., carcinogenic). These chemicals are also regulated by the Safe Drinking Water Act, although the fracturing industry is almost exempt from this Act. We partition the fracking counties into high and low groups based on the quartile value of the number of toxic chemicals disclosed in each county and retain the top and the bottom quartiles. We then rerun equation (1) by replacing the DID estimator with non-overlapping partitions marking observations in the post-period in the respective group.

[24] The report is available at http://ecolo.org/documents/documents_in_english/gas-_Hydraulic-Fract-chemicals-2011-report.pdf. In this report, the US House of Representatives Committee on Energy and Commerce identify 29 toxic chemicals and 7 commonly used chemicals. 8 of the toxic chemicals are Safety Water Drinking Act contaminants that impose risk to the public drinking water system, and the remaining 21 are Hazardous Air Pollutants that do not impose risk to the public drinking water system. Since the fracking fluid contaminates water but not air, we only deem the 8 Safety Water Drinking Act contaminants as toxic. Regarding the commonly used chemicals, 2-butoxyethanol (2-BE) is separately discussed and has been detected in drinking water by EPA. According to EPA scientists, exposure to 2-BE can destruct red blood cells and damage to the spleen, liver, and bone marrow. Therefore, we additionally consider 2-BE as toxic.

Table 6 column (1) reports the results. The coefficient on the DID estimator is positive and significant for the high group. On average, bottled water sales increase by approximately 14.9 percent for counties that disclose a larger number of toxic chemicals in the post-disclosure period. We find significant but weaker results for the lower quartile group (approximately 5.2 percent). These findings are consistent with the intuition that the public perceives a higher risk associated with toxic chemicals and thus reacts more strongly to the disclosure.

The mandatory chemical disclosure program does not release the identity of all chemicals. To protect their proprietary knowledge, operators are allowed to withhold the identity of chemicals deemed as trade secrets. Jiang (2024) finds that approximately 16 percent of the chemicals are labeled as trade secrets, and operators may strategically withhold non-proprietary chemicals as trade secrets. Recent media articles also point out that operators have withheld the disclosure of dangerous "forever chemicals" in their operations because of trade secret claims.[25] Therefore, we also examine how the public perceives and reacts to these trade secret chemicals. Similar to our analyses for toxic chemicals, we partition the fracking counties into high and low groups based on the quartile value of the number of trade secret chemicals disclosed in each county and rerun equation (1).

Table 6 column (2) presents the results for trade secret chemicals. The coefficient on the DID estimator is insignificant for both high and low groups. One possible explanation is that public response to trade secret chemicals may jointly depend on the presence of toxic chemicals. For instance, in counties where operators use more toxic chemicals, the public may have already taken into consideration the impact of toxic chemicals, and thereby reducing the (additional) impact of trade secrets disclosures on avoidance behavior.

[25] Forever chemicals, such as PFAS (Perfluorooctanoic Acid), are resistant to water, grease, and heat, and they have long-lasting environmental and health effects.

To explore this possibility, we split the treatment counties based on the median number of toxic chemicals and then partition each subsample into high and low subgroups based on the number of trade secret chemicals (*Secrets_high* and *Secrets_low* for treatment counties that use more toxic chemicals and *Secrets_high* and *Secrets_low* for treatment counties that use fewer toxic chemicals) and focus on the two extreme quartiles. Table 6 columns (3)-(4) report the findings for the subsample test. For counties that use more toxic chemicals, we find that the avoidance behavior is about two times stronger in the high group (reports more trade secrets) compared with that in the low group (reports fewer trade secrets). However, the difference between them is not statistically significant. Regarding counties that use fewer toxic chemicals, we only document avoidance behavior in counties with a higher level of trade secrets. The coefficient on the DID estimator is insignificant when operators neither use a high level of toxic nor trade secret chemicals. Overall, these results generally support the idea that the public perceives higher risks associated with fracking when local operators use more toxic chemicals or label more chemicals as trade secrets. These findings also imply that the nature of the disclosed information has been rationally incorporated into the public's decision-making process.

6. ADDITIONAL ANALYSES

In this section, we investigate whether the documented behavioral change varies by household and demographic characteristics. We first examine their past experiences of dealing with water quality issues. Our temporal analyses suggest that fracking counties do not receive more frequent water quality violation notices over time. However, for counties that received notices more frequently during the pre-disclosure period, households may have already become more aware of drinking water issues. These public notices often contain information about water quality problems and the associated solutions (e.g., using bottled water). As a result, residents in these counties may have already altered their water consumption habits or installed treatment facilities even before the launch of fracking disclosures. For each treatment county in the pre-disclosure period, we take the sum of *Tier1_violation* and *Tier2_violation* and average it across the total number of pre-disclosure weeks. This enables us to determine the extent to which a county received a Tier 1 or Tier 2 violation notice in the pre-disclosure period. We then split the treatment counties into two non-overlapping groups based on the quartile value of this measure and focus on the top and the bottom quartiles. On average, the high group experienced violations for approximately 43 percent of the pre-disclosure weeks, while the low group did not experience any violations in the pre-disclosure period. Table 7 column (1) suggests that our main results stem from fracking counties that *did not* frequently receive water quality violation notices in the pre-disclosure period.

We also examine whether more intensive exposure to fracking activity results in stronger avoidance behavior. We measure fracking exposure by calculating the ratio of the total number of HF wells to the average population in the post-disclosure period, divided by the land area (km^2) of each fracking county. This gives us the number of HF wells per capita per unit of land area. We then split the fracking counties into two groups based on whether the fracking exposure is above the upper quartile or below the lower quartile in the post-disclosure period. Table 7 column (2) reports the findings. We find that the increase in water consumption stems from households with more intense exposure to fracking activities in the post-disclosure period.

6.2 Demographic Characteristics

Next, we turn to demographic characteristics to explore the key factors that drive avoidance behavior. One key assumption in our paper is that, on average, the public is more risk-averse when there is uncertainty about their pollution exposure. We first explore whether the behavioral response varies between communities with different levels of risk preference.

Prior scientific studies primarily focus on the impact of fracking on the elderly and children because these groups are more vulnerable to the potential health risks associated with fracking activities (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022). The elderly and children are often considered at-risk populations who are more reluctant to be exposed to pollution. We obtain data on the population aged above 65 and below 5 years old in each county from the American Community Survey. Similar to our demographic controls, we use the five-year estimates that cover most counties. We first calculate the fraction of residents above 65 and below 5 years old in each county for each year. We then partition the fracking counties into high and low groups based on the quartile value of the number and drop the middle two quartiles. In Table 8 column (1), we find that the increase in bottled water sales is positive and significant for fracking counties with a higher fraction of at-risk populations. We find weaker results for counties with a smaller fraction of at-risk populations. These results provide support that the vulnerable group is more risk-averse regarding the health risks associated with fracking chemicals.

We also provide more direct evidence that the avoidance behavior is driven by low-risk tolerance regarding health risks. We proxy health risk tolerance by the community's preventative action during the COVID-19 outbreak, a major public health event. We focus on COVID-19 vaccines as a preventative measure, which are available for free to everyone living in the US, regardless of immigration or insurance status.[26] Nevertheless, there was a lot of uncertainty surrounding the severity of the disease when the pandemic started. Individuals with higher levels of risk tolerance perceive COVID-19 as a less severe illness with a lower likelihood of severe outcomes. This led to a different attitude towards receiving vaccines when the vaccines were first rolled out. We expect that the avoidance behavior is stronger in communities that are more willing to receive COVID-19 vaccines when they become available. We obtain historical vaccination records for each county from the CDC and exploit the

[26] Although there are some concerns regarding the side effects of the vaccine, the Centers for Disease Control and Prevention (CDC) recommends that everyone ages 6 months and older in the US receive the vaccine for the prevention of COVID-19. See the details of CDC's recommendation from https://www.cdc.gov/vaccines/covid-19/clinical-considerations/interim-considerations-us.html.

variation in the administration rate when the COVID-19 vaccines first rolled out (the first month) in each county. We then partition the fracking counties into high and low groups based on the quartile value of the administration rate. In Table 8 column (2), we find evidence consistent with our expectations. After firms start making fracking disclosures, bottled water sales increase by approximately 22 percent in counties where residents are more willing to receive the first dose vaccine. However, we do not find significant results for the low group. Overall, these findings are consistent with low-risk tolerance driving avoidance behavior.

Another interesting question is how the documented behavior change varies between families with different income levels. On the one hand, wealthier families might have a stronger willingness to pay for clean water and thus allocate more economic resources to pollution prevention when pollution transparency is enhanced. However, since bottled water is relatively affordable, the difference in their response may not be significant. In Table 8 column (3), we partition the treatment counties into two non-overlapping groups based on the median household income level. Interestingly, we only find a significant increase in bottled water consumption for counties with a lower income level. The null result for wealthier counties might be due to preventative actions taken before the fracking disclosure or other avoidance strategies that are more expensive but not captured in our study.

Finally, we consider the job characteristics of residents. Fracking disclosure contains industry-specific information that may not be well-noticed or fully understood by the general public. We argue that industry-specific information is better incorporated by residents who work in the same industry. This is because employees from the same industry are more likely to possess industry-specific knowledge and pay attention to the release of information. Some of the counties are large fracking towns where nearly a quarter of the residents work in the extraction industry.[27] The county-year level employment data are from the Census Bureau's

[27] This is based on the authors' calculation using data from the Census Bureau's annual County Business Pattern.

annual County Business Pattern (CBP).[28] For each county, we compute the fraction of employees employed by the extraction sector in each year based on 3-digit NAICS codes (211) of the facilities located in that county. We then partition the fracking counties into high and low groups based on the quartile value of sectoral employment. In Table 8 column (4), we find that the avoidance behavior is more prominent for counties with a higher fraction of employees employed in the extraction industry. These results are in line with the notion that industry exposure is a key determinant of internalizing industry-specific information.

7. PUBLIC HEALTH CONSEQUENCES

A valid concern regarding our main results is that the observed avoidance behavior may simply reflect public panic. Although the avoidance behavior reduces the perceived risks associated with water quality, it is unclear whether such behavioral changes translate into actual improvements in health outcomes. To shed light on this question, we examine the potential health consequences of avoidance behavior. However, given the challenges in estimating the health effects of fracking (Hill and Ma, 2022), the results presented in this section are merely suggestive and should be interpreted with caution.

As the existing evidence primarily focuses on the effect of HF practices on infant health (i.e., birth weight) (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022), we follow this literature and examine whether the launch of fracking disclosure increases the average birth weight in fracking counties. We obtain information on the monthly average birth weight for newborns in each county from the CDC WONDER Online Databases. We are able to find birth records for approximately 33 percent (20 percent) of our fracking (control) counties. The mean monthly

[28] Since approximately 50 percent of employment counts are masked to prevent disclosure in CBP, we use the CBP establishment counts by employee size class information to impute employment counts. Specifically, a county's employment count for a masked industry is imputed as $\sum_s Establishment_{js} \times (\frac{MaxEmployeeSize_s + MinEmployeeSize_s}{2})$ where $Establishment_{js}$ is the number of industry j's establishments in employee size class s, and $Max(Min)EmployeeSize_s$ is the upper (lower) end of the employee count range of employee size class s.

average birth weight is 3,255.61 grams for the full sample (with 3,234.75 grams and 3,270.41 grams for fracking and non-fracking counties, respectively).

Table 9 presents the results for the effect of fracking disclosure on infant birth weight.[29] In column (1), the coefficient on the DID estimator is highly significant and positive, suggesting an overall improvement in public health. Column (2) shows that the health improvement is more prominent for fracking counties that experience a larger increase in bottled water sales after the fracking disclosure. On average, the birth weight of newborns in these counties increased by approximately 11 grams. Hill and Ma (2022) report that each HF well is associated with a reduction in birth weight of approximately 25 grams. Thus, the estimated increase in column (2) is arguably economically meaningful. Overall, these results suggest that consuming bottled water might help mitigate the negative consequences of fracking on infant health (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022).

8. CONCLUSION

In this paper, we examine how corporate environmental disclosure affects pollution avoidance behavior by the general public. We exploit a landmark policy change in the U.S. fracking industry that mandates operators to disclose the use of chemicals in their fracking operations. We document that fracking disclosure leads to increased defensive spending as reflected in higher bottled water sales. We also find that this avoidance response is more pronounced in states where disclosure is required to be on an easy-to-access platform, and when the media and the public pay more attention to fracking-related issues. These findings highlight the role of information acquisition, awareness, and integration in eliciting avoidance behaviors. We further find that the avoidance response is stronger when the public is exposed

[29] All models include the same set of control variables as in equation (1). Since fracking also negatively affects infant birth weight via air pollution (Currie et al., 2017; Hill, 2018; Hill and Ma, 2022), we further control for drilling intensity using the number of wells drilled in each county each year. We use county fixed effects and year-month fixed effects and cluster the standard errors at the state level.

to higher levels of toxic or secret chemicals, suggesting that the behavioral change is triggered by a heightened degree of perceived risks. We document significant heterogeneity in the public's avoidance behavior based on various household and demographic characteristics: households that previously were not alerted to tap water violations and those with more intense exposure to fracking react more strongly; and avoidance behavior is more pronounced among vulnerable populations, risk-averse communities, lower-income families, and individuals working in the extractive industry. Finally, we provide suggestive evidence that avoidance behavior contributes to better public health outcomes.

Our study contributes to the environmental disclosure literature by shifting the focus from firms' responses to disclosure regulations to behavioral adjustments by the general public. Prior research primarily emphasizes how disclosure regulations influence firms' pollution practices and environmental quality (Bonetti et al., 2024; Fetter, 2022). Despite firms' efforts, pollution remains inevitable and pervasive across communities. We complement these studies by providing evidence that mandatory environmental disclosures, which increase transparency about previously hidden polluting operations, empower the public to take preventive actions to reduce health risks associated with pollution. This highlights an often-underexplored channel through which disclosure regulations mitigate the negative externalities of corporate pollution, beyond firms' own regulatory or reputation-driven incentives to internalize those externalities. By documenting how increased transparency drives public awareness and health-risk mitigation, our findings underscore the broader societal value of information-based approaches in environmental regulation.

We acknowledge two key limitations of our analyses. First, our measure of avoidance behavior is incomplete because bottled water consumption captures only one of the many possible actions that residents can take to avert risks. As such, our estimate likely represents only a lower bound of overall avoidance behavior. Second, we do not conduct a comprehensive cost-benefit analysis of the disclosure regulation. While the costs of avoidance, such as defensive spending, welfare loss from forgone consumption, and the environmental impact of plastic waste, are relatively straightforward to quantify, estimating the benefits of disclosure regulations is more complex and requires precise identification of the health improvements resulting from behavioral changes. Nevertheless, such an analysis would offer valuable insights by enabling a first-pass comparison between information-based environmental regulations and more traditional command-and-control or incentive-based approaches. We leave this important question to future research.

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Figures

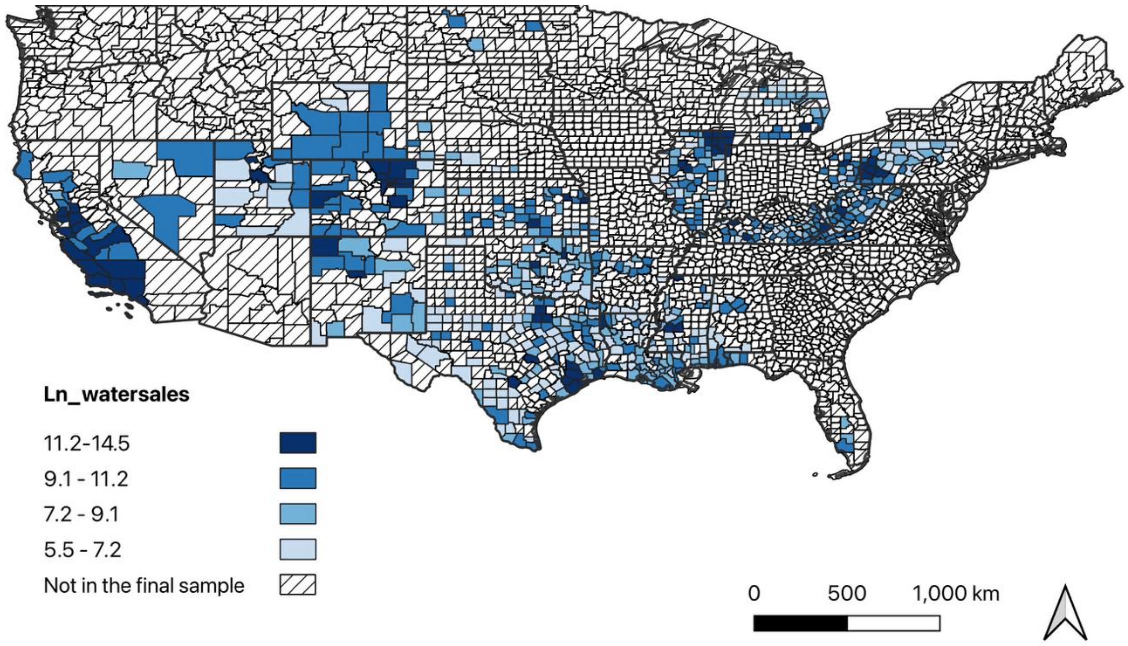

Figure 1a: Average County-Level Bottled Water Sales During 2006-2019

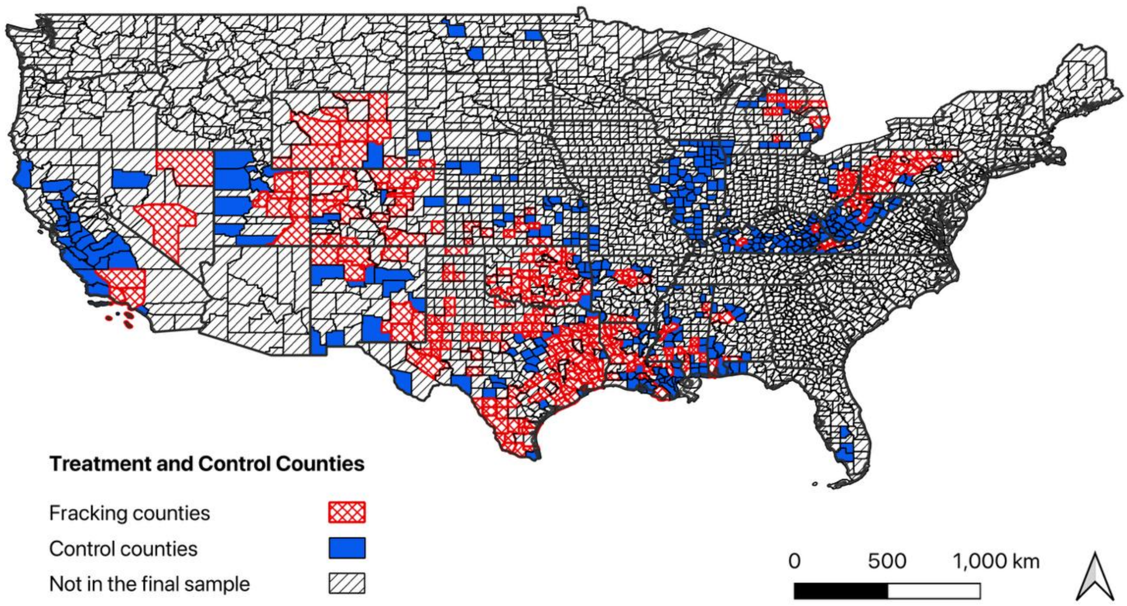

Figure 1b: Fracking (Treatment) Counties and Control Counties

Note: The map in Figure 1a shows county-week-level average bottled water sales during the 2006-2019 study period (in 2019 dollars; log-transformed) in the contiguous United States. Counties without sales data in the NielsenIQ database are not included in the sample. The final sample covers 640 counties in the US. Figure 1b illustrates the treatment and control counties.

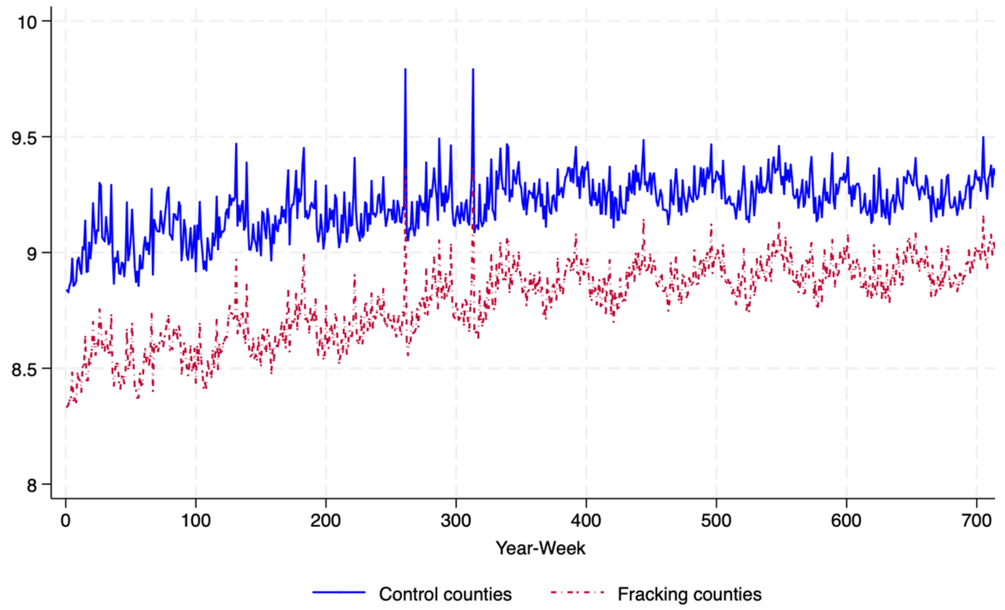

Figure 2a: Week-Level Bottled Water Sales During 2006-2019

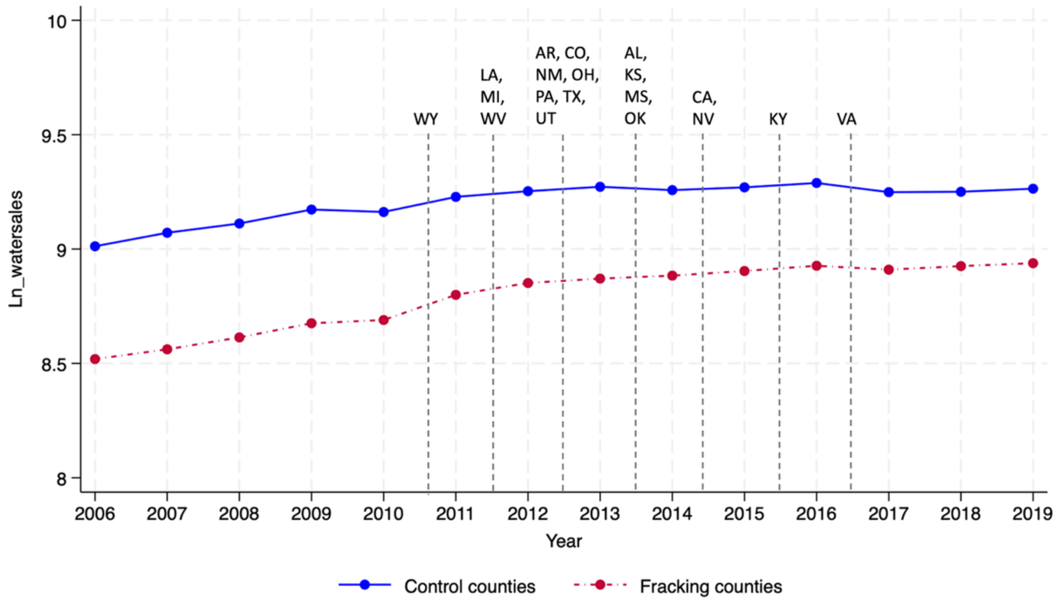

Figure 2b: Year-Level Bottled Water Sales During 2006-2019

Note: Figure 2a depicts county-week-level average bottled water sales for the treatment (solid line) and control (dotted line) groups during the 2006-2019 study period (in 2019 dollars; log-transformed). Figure 2b shows the trend at the county-year level as well as the disclosure mandate entry-into-force years for states with disclosure laws.

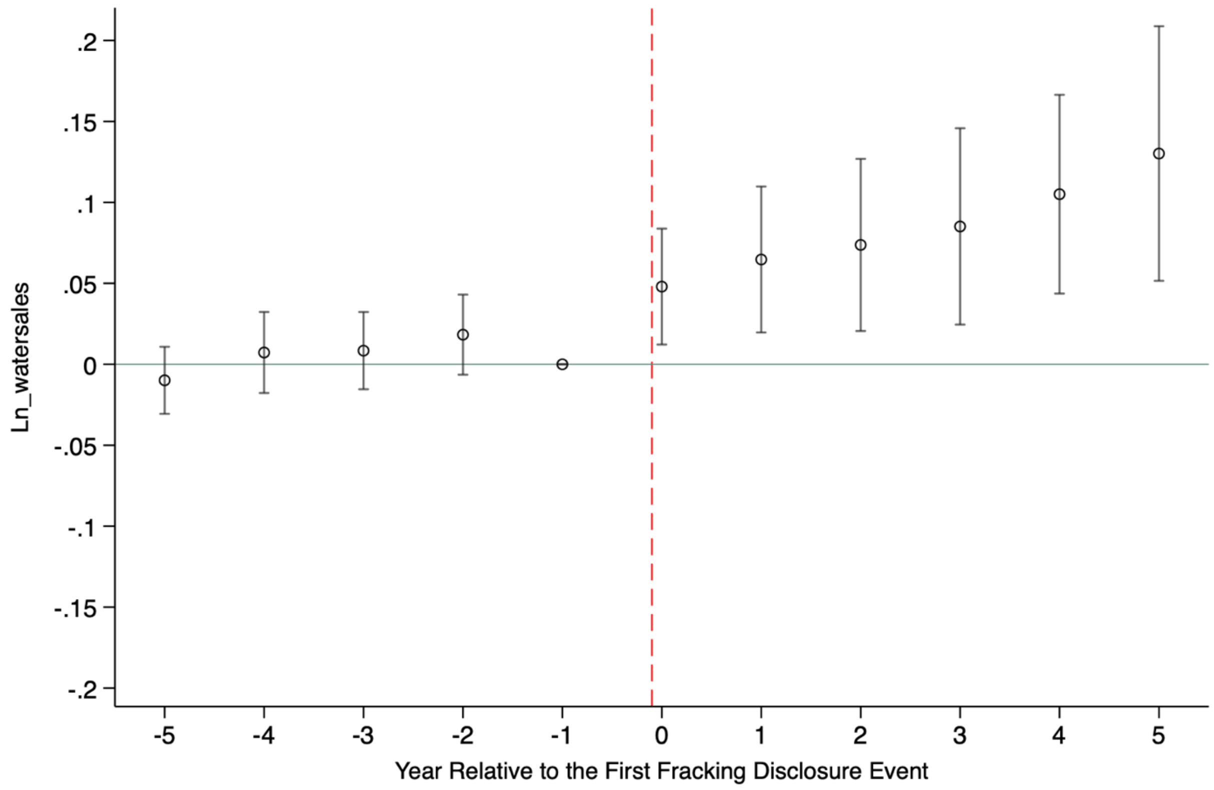

Figure 3: Dynamic Effect of Fracking Disclosure on Bottled Water Sales

Note: Figure 3 plots the dynamic effect of the coefficients from the estimation of Eq. (1), along with the respective 90% confidence intervals. The dependent variable is bottled water sales (log-transformed). *Year -1* comprises bottled water sales made within the 52 weeks (1 year) before the first fracking disclosure event in the focal fracking county. *Year 5* comprises bottled water sales made 260 weeks and beyond (5 years and beyond) after the first fracking disclosure event in the focal fracking county. *Year -1* is omitted from the regression and serves as a benchmark.

Tables – Table 1: Summary Statistics

Panel A: Full sample

	N	Mean	p10	p25	p50	p75	p90	SD
Watersales	466,053	71,051.527	718.667	1,406.310	7,516.984	35,767.535	108,178.289	341,405.444
Ln_watersales	466,053	9.007	6.579	7.249	8.925	10.485	11.592	1.992
Disclosure	466,053	0.223	0.000	0.000	0.000	0.000	1.000	0.417
Tier1_violation	466,053	0.047	0.000	0.000	0.000	0.000	0.000	0.212
Tier2_violation	466,053	0.188	0.000	0.000	0.000	0.000	1.000	0.391
Ln_income	466,053	10.766	10.461	10.616	10.759	10.906	11.086	0.248
Ln_population	466,053	10.777	9.388	9.927	10.584	11.452	12.499	1.227
Ln_population_sq	466,053	117.641	88.131	98.551	112.028	131.144	156.227	27.720
Precipitation	466,053	2.757	0.193	0.500	1.649	3.886	6.838	3.146
Temperature	466,053	14.607	1.010	7.452	15.585	22.563	26.816	9.670
Birth_weight	106,582	3,255.506	3,157.660	3,207.650	3,260.090	3,308.590	3,346.950	77.103

Panel B: By treatment and control group

	Fracking counties (treatment group)				*Non-Fracking O&G counties (control group)*			
	N	Mean	p50	SD	N	mean	p50	SD
Watersales	222,963	75,724.690	5,278.399	420,071.341	243,090	66,765.286	10,881.530	248,147.572
Ln_watersales	222,963	8.791	8.572	2.009	243,090	9.205	9.295	1.954
Disclosure	222,963	0.467	0.000	0.499	243,090	0.000	0.000	0.000
Tier1_violation	222,963	0.063	0.000	0.243	243,090	0.033	0.000	0.178
Tier2_violation	222,963	0.206	0.000	0.405	243,090	0.171	0.000	0.376
Ln_income	222,963	10.780	10.767	0.217	243,090	10.754	10.751	0.273
Ln_population	222,963	10.698	10.584	1.198	243,090	10.848	10.585	1.249
Ln_population_sq	222,963	115.891	112.011	27.070	243,090	119.247	112.044	28.208
Precipitation	222,963	2.540	1.402	3.056	243,090	2.956	1.896	3.214
Temperature	222,963	15.012	15.920	9.827	243,090	14.236	15.265	9.509
Birth_weight	44,218	3,234.598	3,236.790	74.116	62,364	3,270.331	3,279.010	75.733

Note: This table presents the descriptive statistics for the key variables. Panel A reports statistics for the full sample. Panel B reports statistics for the treatment and the control group, respectively. The definitions of the variables are available in the Appendix.

Table 2: Main Results

	(1)	(2)
	Ln_watersales	*Ln_watersales*
Disclosure	0.105**	0.082**
	(0.039)	(0.032)
Tier1_violation		0.052***
		(0.014)
Tier2_violation		0.032**
		(0.012)
Ln_income		0.540***
		(0.129)
Ln_population		8.265***
		(2.563)
Ln_population_sq		-0.374***
		(0.108)
Precipitation		-0.004***
		(0.001)
Temperature		0.006***
		(0.001)
N	466,053	466,053
County FE	YES	YES
Year-Week FE	YES	YES
Adjusted R-squared	0.985	0.985

Note: This table reports OLS coefficients estimating Eq. (1) to assess the impact of fracking disclosure on bottled water sales. The dependent variable is bottled water sales (log-transformed). The key variable of interest is *Disclosure*, which is a binary variable indicating the post-disclosure period in the treatment counties. Columns (1)-(2) report the results without and with control variables, respectively. All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 3: Robustness Checks

Panel A: Alternative regression methods and treatment group

	Stacked regression (Cengiz et al., 2019)		Entropy balanced		Alternative approach to defining treatment county			
					Distance-based		*HUC10-based*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln_watersales	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*
Disclosure	0.083***	0.088***	0.093**	0.077**	0.096**	0.073**	0.082*	0.065†
	(0.021)	(0.021)	(0.035)	(0.031)	(0.043)	(0.035)	(0.047)	(0.041)
N	1,992,483	1,992,483	466,053	466,053	466,053	466,053	466,053	466,053
Controls	NO	YES	NO	YES	NO	YES	NO	YES
Cohort × County FE	YES	YES	NO	NO	NO	NO	NO	NO
Cohort × Year-Week FE	YES	YES	NO	NO	NO	NO	NO	NO
County FE	NO	NO	YES	YES	YES	YES	YES	YES
Year-Week FE	NO	NO	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.981	0.982	0.984	0.985	0.984	0.985	0.984	0.985

Panel B: Alternative dependent variable

	Bottled water sales per capita		Total volume of bottled water		Average unit price of bottled water		Juice, milk, coffee and liquor	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln_waterpc	*Ln_waterpc*	*Ln_watervol*	*Ln_watervol*	*Ln_waterprice*	*Ln_waterprice*	*Ln_jmclsales*	*Ln_jmclsales*
Disclosure	0.075**	0.070**	0.075**	0.062**	0.011	0.009	0.065	0.035
	(0.031)	(0.029)	(0.033)	(0.027)	(0.007)	(0.006)	(0.088)	(0.070)
N	466,053	466,053	466,053	466,053	466,053	466,053	466,053	466,053
Controls	NO	YES	NO	YES	NO	YES	NO	YES
County FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-Week FE	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-squared	0.968	0.970	0.986	0.986	0.811	0.813	0.983	0.983

Note: This table reports the results of robustness checks. Panel A reports the results in Table 2, columns (1)-(2), using alternative regression methods and alternative treatment groups. The dependent variable is bottled water sales (log-transformed). The key variable of interest is *Disclosure*, which is a binary variable indicating the post-disclosure period in the treatment counties. Columns (1)-(2) present the results for the stacked regression model. Columns (3)-(4) present the results after entropy balancing. In columns (5)-(6), we assume the neighbor control county is also a treatment county if there is at least one HF well drilled within 5 km of the county border. In columns (7)-(8), we assume a control county as a treatment county if it is located within the same watershed (HUC 10) as an HF county. Models in columns (1)-(2) include cohort × county fixed effects and cohort × year-week fixed effects. Models in columns (3)-(8) include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by cohort × state in columns (1)-(2) and by state in columns (3)-(8). Panel B reports the results in Table 2, columns (1)-(2), using alternative dependent variables. The dependent variable in columns (1)-(2) is bottled water sales scaled by county-level population (log-transformed). The dependent variable in columns (3)-(4) is the total volume of bottled water (log-transformed). The dependent variable in columns (5)-(6) is the average unit price of bottled water adjusted for CPI (log-transformed). The dependent variable in columns (7)-(8) is the sales of juice, milk, coffee and liquor (log-transformed). All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. †, *, **, *** denote statistical significance at the 15%, 10%, 5%, and 1% level (two-tailed), respectively.

Table 4: Mechanism – Information Acquisition

	Default filing platform	FracFocus platform upgrade
	(1)	(2)
	Ln_watersales	*Ln_watersales*
Disclosure × FracFocus_mandatory	0.105**	
	(0.042)	
Disclosure × FracFocus_voluntary	-0.001	
	(0.037)	
Disclosure × FFscore		0.018***
		(0.006)
Disclosure		0.046
		(0.029)
p-value of diff. in coefficients	0.132	NA
Disclosure × FFscore + Disclosure = 0	NA	0.046
N	466,053	466,053
Controls	YES	YES
County FE	YES	YES
Year-Week FE	YES	YES
Adjusted R-squared	0.985	0.985

Note: This table reports the results for the role of information acquisition in nudging avoidance behavior. The dependent variable is bottled water sales (log-transformed). In column (1), we split the treatment group based on the default filing platform required by each state when the state disclosure laws were enacted (i.e., whether reporting to FracFocus is mandatory). Column (2) reports the results for platform improvement. *FFscore* is a time-varying variable and is increased by one for the periods after FracFocus underwent a major upgrade. All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 5: Mechanism – Information Awareness and Integration

	Increase in media coverage	Increase in Google search
	(1)	(2)
	Ln_watersales	*Ln_watersales*
Disclosure × ΔMedia_high	0.132**	
	(0.058)	
Disclosure × ΔMedia_low	-0.042	
	(0.039)	
Disclosure × ΔGtrend_high		0.126**
		(0.056)
Disclosure × ΔGtrend_low		-0.021
		(0.078)
p-value of diff. in coefficients	0.035	0.182
N	394,200	394,513
Controls	YES	YES
County FE	YES	YES
Year-Week FE	YES	YES
Adjusted R-squared	0.986	0.985

Note: This table reports the results for the role of information awareness and integration in nudging avoidance behavior. The dependent variable is bottled water sales (log-transformed). In columns (1)-(2), we split the treatment group into two subsamples based on the quartile value of the change in state-year level media coverage of fracking-related topics and state-year level Google search of the term "fracking" before and after the first fracking disclosure event (the middle two quartiles are dropped from the treatment sample). All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 6: Mechanism – Change in Risk Perception

	Number of toxic chemicals	Number of trade secrets	Number of trade secrets *Number of toxic chemicals above median*	Number of trade secrets *Number of toxic chemicals below median*
	(1)	(2)	(3)	(4)
	Ln_watersales	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*
Disclosure × Toxic_high	0.139**			
	(0.066)			
Disclosure × Toxic_low	0.051**			
	(0.021)			
Disclosure × Secrets_high		0.069	0.184**	0.101***
		(0.056)	(0.075)	(0.035)
Disclosure × Secrets_low		0.048	0.141***	0.006
		(0.032)	(0.050)	(0.040)
p-value of diff. in coefficients	0.149	0.678	0.593	0.060
N	372,248	355,458	298,883	299,300
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year-Week FE	YES	YES	YES	YES
Adjusted R-squared	0.985	0.985	0.984	0.985

Note: This table reports the results for whether the heightened risk perception nudges avoidance behavior. The dependent variable is bottled water sales (log-transformed). In columns (1)-(2), we split the treatment group into two subsamples based on the quartile value of county-level number of toxic chemicals and trade secret chemicals (the middle two quartiles are dropped from the treatment sample). In columns (3)-(4), we first split the treatment sample based on the median of the number of toxic chemicals and rerun the subsample test for trade secret chemicals in column (2). All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 7: Pre-disclosure Violation Experience and Post-disclosure Fracking Exposure

	Frequency of receiving public notices during the pre-period	# of HF well per capita per sq. km during the post-period
	(1)	(2)
	Ln_watersales	*Ln_watersales*
Disclosure × Pre_violation_high	0.016	
	(0.052)	
Disclosure × Pre_violation_low	0.091**	
	(0.034)	
Disclosure × Post_exposure_high		0.217***
		(0.076)
Disclosure × Post_exposure_low		0.011
		(0.030)
p-value of diff. in coefficients	0.252	0.025
N	405,567	359,890
Controls	YES	YES
County FE	YES	YES
Year-Week FE	YES	YES
Adjusted R-squared	0.985	0.985

Note: This table reports the effect of past tap water violations experience and current exposure to fracking on nudging avoidance behavior. The dependent variable is bottled water sales (log-transformed). In columns (1)-(2), we split the treatment group into two subsamples based on the quartile value of past tap water violation frequency and current fracking exposure (the middle two quartiles are dropped from the treatment sample). Past tap water violation frequency is measured by the total number of weeks under Tier 1 or Tier 2 violations in the pre-disclosure period divided by the total number of pre-disclosure weeks. Current fracking exposure is measured by the ratio of the total number of HF wells to the average population in the post-disclosure period, scaled by the land area (km^2) of each fracking county. All models include county fixed effects and year-week fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 8: Demographic Characteristics

	Fraction of elderly and children	COVID 1st dose vaccine	Household income	Fraction of O&G employment
	(1)	(2)	(3)	(4)
	Ln_watersales	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*
Disclosure × Vulnerable_high	0.208***			
	(0.053)			
Disclosure × Vulnerable_low	0.055*			
	(0.028)			
Disclosure × Vaccine_high		0.202***		
		(0.034)		
Disclosure × Vaccine_low		-0.016		
		(0.054)		
Disclosure × Income_high			0.020	
			(0.036)	
Disclosure × Income _low			0.123**	
			(0.051)	
Disclosure × Employ_high				0.140*
				(0.069)
Disclosure × Employ_low				0.013
				(0.025)
p-value of diff. in coefficients	0.004	0.001	0.106	0.028
N	354,523	347,115	354,577	379,225
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year-Week FE	YES	YES	YES	YES
Adjusted R-squared	0.987	0.987	0.986	0.985

Note: This table reports the heterogeneity in treatment effects based on demographic characteristics. The dependent variable is bottled water sales (log-transformed). We split the treatment group into two subsamples based on the quartile value of the percentage of the population with an age above 65 or below 5, the administration rate of the 1st dose COVID vaccine, the median household income level, and the percentage of the population employed in the extraction sector. All models include county fixed effects and year-week fixed effects (the middle two quartiles are dropped from the treatment sample). Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Table 9: The Effect of Avoidance Behavior on Infant Birth Weight

	Pooled sample	Increase in bottled water sales
	(1)	(2)
	Birth_weight	*Birth_weight*
Disclosure	5.052*	
	(2.860)	
Disclosure × ΔLn_watersales_high		10.976**
		(4.786)
Disclosure × ΔLn_watersales_low		4.539
		(3.900)
p-value of diff. in coefficients	NA	0.053
N	106,582	86,142
Controls	YES	YES
County FE	YES	YES
Year-Month FE	YES	YES
Adjusted R-squared	0.668	0.657

Note: This table reports the results for public health consequences. The dependent variable is the monthly average birth weight for each county. Column (1) reports the results of the effect of fracking disclosure on infant birth weight. In column (2), we split the treatment group into two subsamples based on the quartile value of the change in bottled water sales in fracking counties before and after the first fracking disclosure event (the middle two quartiles are dropped from the treatment sample). We further control for drilling intensity in all models (number of wells drilled in each county each year). All models include county fixed effects and year-month fixed effects. Standard errors (in parenthesis) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are reported. *, **, *** denote statistical significance at the 10%, 5%, and 1% level (two-tailed), respectively.

Appendix A: Variable Definition

Variable Name	Description	Source
Ln_watersales	Aggregate county-week level sales in dollars from January 1, 2006, to December 31, 2019 (in 2019 dollars, log-transformed) for all Universal Product Codes representing bottled water. Stores included are those consistently reporting sales data in all weeks during 2006-2019.	NielsenIQ Retail Scanner
Disclosure	A binary indicator equal to 1 for weeks in the post-disclosure period in fracking counties (0 for weeks in the pre-disclosure period in fracking counties and for all weeks in control counties).	FracFocus and Well Database
Tier1_violation	A binary indicator marking weeks under violations due to contaminants with an immediate health risk, such as pathogens and nitrate.	EPA Safe Drinking Water Information Systems and Allaire et al. (2019)
Tier2_violation	A binary indicator marking weeks under violations when water systems fail to comply with other requirements, such as MCL rules (Maximum Contaminant Level).	EPA Safe Drinking Water Information Systems and Allaire et al. (2019)
Ln_income	Median household income in each county each year (end year of the five-year estimates). For 2006, 2007, and 2008, we use the 2005-2009 estimates because the multiyear data are not available before 2009.	American Community Survey
Ln_population	Median household population in each county each year (end year of the five-year estimates). For 2006, 2007, and 2008, we use the 2005-2009 estimates because the multiyear data are not available before 2009.	American Community Survey
Ln_population_sq	Squared of Ln_population.	
Precipitation	Weekly average of daily precipitation in each county.	Wolfram Schlenker's website (based on PRISM dataset)
Temperature	Weekly average of daily temperature (average of minimum and maximum daily temperatures) in each county.	Wolfram Schlenker's website (based on PRISM dataset)
Ln_waterpc	Aggregate county-week level bottled water sales from January 1, 2006, to December 31, 2019, scaled by county-level population (in 2019 dollars, log-transformed).	NielsenIQ Retail Scanner and American Community Survey
Ln_watervol	Volume of bottled water sold by county and week from January 1, 2006, to December 31, 2019 (standardized to milliliters, log-transformed).	NielsenIQ Retail Scanner

Ln_waterprice	Average price of bottled water sold by county and week from January 1, 2006, to December 31, 2019 (in 2019 dollars, log-transformed).	NielsenIQ Retail Scanner
Ln_jmclsales	Aggregate county-week level sales in dollars from January 1, 2006, to December 31, 2019 (in 2019 dollars, log-transformed) for all Universal Product Codes representing juice, milk, coffee and liquor. Stores included are those consistently reporting sales data in all weeks during 2006-2019.	NielsenIQ Retail Scanner
FracFocus_mandatory (voluntary)	A binary indicator equal to one if reporting to FracFocus is mandatory (voluntary) in a state when the state law became effective.	FracFocus, EPA and state websites
FFscore	Time-varying variable increased by one for the periods after FracFocus underwent a major upgrade (ranging from 0-3). See footnote 13 for the complete timeline.	FracFocus
ΔMedia_high(low)	A binary indicator equals one if the change in state-year level media coverage of fracking-related topics (headline that includes “fracking” AND “pollution” or “health” or “water” or “contaminant” or and their variants) before and after the first fracking disclosure event was higher (lower) than the 75th (25th)percentile across all fracking counties.	LexisNexis
ΔGtrend_high(low)	A binary indicator equals one if the change in state-year level Google search of the term “fracking” before and after the first fracking disclosure event was higher (lower) than the 75th (25th) percentile across all fracking counties.	Google search
Toxic_high(low)	A binary indicator equals one if the number of toxic chemicals used was higher (lower) than the 75th (25th) percentile across all fracking counties.	FracFocus and the US House of Representatives Committee on Energy and Commerce
Secrets_high(low)	A binary indicator equals one if the number of trade secret chemicals used was higher (lower) than the 75th (25th) percentile across all fracking counties.	FracFocus
Pre_violation_high(low)	A binary indicator equals one if the ratio of the total number of weeks under Tier 1 or Tier 2 violations in the pre-disclosure period divided by the total number of pre-disclosure weeks was higher (lower) than the 75th (25th) percentile across all fracking counties.	EPA Safe Drinking Water Information Systems and Allaire et al. (2019)
Post_exposure_high(low)	A binary indicator equals one if the ratio of the total number of HF wells to the average population in the post-disclosure period, scaled by the land area (km^2) was higher (lower) than the 75th (25th) percentile across all fracking counties.	FracFocus and Census Bureau

Vulnerable_high(low)	A binary indicator equals one if the percentage of the population with an age above 65 or below 5 was higher (lower) than the 75^{th} (25^{th}) percentile across all fracking counties.	American Community Survey
Vaccine_high(low)	A binary indicator equals one if the administration rate of the 1st dose COVID vaccine was higher (lower) than the 75^{th} (25^{th}) percentile across all fracking counties.	Centers for Disease Control and Prevention (CDC)
Income_high(low)	A binary indicator equals one if the median household income level was higher (lower) than the 75^{th} (25^{th}) percentile across all fracking counties.	American Community Survey
Employ_high(low)	A binary indicator equals one if the percentage of the population employed in the extraction sector was higher (lower) than the 75^{th} (25^{th}) percentile across all fracking counties.	Census Bureau's County Business Patterns
Birth_weight	Monthly average birth weight in each county (in grams).	CDC Wonder Database
ΔLn_watersales_high(low)	A binary indicator equals one if the change in bottled water sales before and after the first fracking disclosure event was higher (lower) than the 75^{th} (25^{th}) percentile across all fracking counties.	NielsenIQ Retail Scanner

Appendix B: Entry-into-force Dates of the State Disclosure Mandates

State	Entry-into-force date	Mandatory report to FracFocus since the law's effective date
Alabama (AL)	9-Sep-2013	Yes
Arkansas (AR)	15-Jan-2012	No
California (CA)	1-Jan-2014	Yes
Colorado (CO)	1-Apr-2012	Yes
Kansas (KS)	2-Dec-2013	Yes
Kentucky (KY)	19-Mar-2015	Yes
Louisiana (LA)	20-Oct-2011	Yes
Michigan (MI)	7-Jun-2011	No
Mississippi (MS)	4-Mar-2013	No
Nebraska (NE)	No statewide law	No
Nevada (NV)	1-Aug-2014	Yes
New Mexico (NM)	15-Feb-2012	No
Ohio (OH)	10-Sep-2012	Yes
Oklahoma (OK)	1-Jan-2013	Yes
Pennsylvania (PA)	16-Apr-2012	Yes
Texas (TX)	1-Feb-2012	Yes
Utah (UT)	1-Nov-2012	Yes
Virginia (VA)	1-Dec-2016	No
West Virginia (WV)	19-Aug-2011	No
Wyoming (WY)	17-Aug-2010	No

Note: This table summarizes the entry-into-force dates and the mandated reporting platforms (based on the dates when state laws were enacted) for all states with fracking counties in our sample.

Appendix C: Example Disclosure Form

Hydraulic Fracturing Fluid Product Component Information Disclosure

Job Start Date:	3/14/2017
Job End Date:	3/25/2017
State:	Texas
County:	Midland
API Number:	42-329-40539-00-00
Operator Name:	Endeavor Energy Resources
Well Name and Number:	Nail Ranch 1-12SL Unit 2 #8LA
Latitude:	31.96006700
Longitude:	-102.13025600
Datum:	NAD83
Federal Well:	NO
Indian Well:	NO
True Vertical Depth:	9,547
Total Base Water Volume (gal):	17,517,066
Total Base Non Water Volume:	0

Frac Focus Chemical Disclosure Registry

GROUNDWATER PROTECTION COUNCIL

Interstate Oil & Gas Compact Commission

Hydraulic Fracturing Fluid Composition:

Trade Name	Supplier	Purpose	Ingredients	Chemical Abstract Service Number (CAS #)	Maximum Ingredient Concentration in Additive (% by mass)**	Maximum Ingredient Concentration in HF Fluid (% by mass)**	Comments
Water	Endeavor Energy	Carrier/Base Fluid					
			Water	7732-18-5	100.00000	89.10615	None
100 Mesh	Advanced Stimulation Technologies	PROPPANT					
			Silica (crystaline)	14808-60-7	100.00000	4.97674	None
White 40/70	Advanced Stimulation Technologies	PROPPANT					
			Silica (crystaline)	14808-60-7	100.00000	4.96644	None
15% HCL	Advanced Stimulation Technologies	HYDROCHLORIC ACID (Uninhibited)					
			Water	7732-18-5	73.00000	0.49380	None
			Hydrogen Chloride	7647-01-0	37.00000	0.25028	None
AFR-805	Advanced Stimulation Technologies	FRICTION REDUCERS					
			Petroleum Hydrotreatetd Light Distillate	64742-47-8	100.00000	0.10132	None
AWRS-101	Advanced Stimulation Technologies	SURFACTANTS					
			Methanol	67-56-1	50.00000	0.04313	None
			2-Butoxyethanol	111-76-2	50.00000	0.04313	None
ASCB-501	Advanced Stimulation Technologies	BREAKERS AND BREAKER CATALYSTS					
			Sodium Chloride	7647-14-5	30.00000	0.01729	None
			Sodium Chlorite	7758-19-2	10.00000	0.00576	None
AIR-301	Advanced Stimulation Technologies	IRON CONTROL ADDITIVES					
			Thioglycol	60-24-2	75.00000	0.00151	None
			Cupric Chloride Dihydrate	10125-13-0	7.00000	0.00014	None
			Ammonia	7664-41-7	5.00000	0.00010	None
APS-101	Advanced Stimulation Technologies	ANTI-SLUDGE ADDITIVES					
			Dodecylbenzenesulfonic Acid	27176-87-0	25.00000	0.00042	None
			Glacial Acetic Acid	64-19-7	25.00000	0.00042	None
			Isopropanol	67-63-0	25.00000	0.00042	None
			Ethylene Glycol Monobutyl Ether	111-76-2	25.00000	0.00042	None
ABC-104	Advanced Stimulation Technologies	BIOCIDES					
			TRIBUTYLTETRADECYL PHOSPHONIUM CHLORIDE	81741-28-8	2.80000	0.00070	None
			Poly[oxyethylene (dimethyliminio)ethylene (dimethyliminio) ethylenedichloride]	31512-74-0	2.20000	0.00056	None
Ingredients shown above are subject to 29 CFR 1910.1200(i) and appear on Material Safety Data Sheets (MSDS). Ingredients shown below are Non-MSDS.							

* Total Water Volume sources may include fresh water, produced water, and/or recycled water
** Information is based on the maximum potential for concentration and thus the total may be over 100%

Note: For Field Development Products (products that begin with FDP), MSDS level only information has been provided.
Ingredient information for chemicals subject to 29 CFR 1910.1200(i) and Appendix D are obtained from suppliers Material Safety Data Sheets (MSDS)

Note: This figure shows an example of fracking fluid chemical disclosure. The chemical identity is provided in the fifth column (Chemical Abstract Service Number).

Online Appendices for "Mandatory Environmental Disclosure and Pollution Avoidance Behavior"

Online Appendix A: Anecdotal evidence – media articles

In Colorado –

Analysis: What's in Larimer County fracking fluid

Published in Coloradian, April 12, 2015. By Sarah Jane Kyle

More than 100 different ingredients have been used at 30 hydraulic fracturing sites in Larimer County since 2012.

Missing from 80 percent of those jobs was an oft-cited cause for health and safety concerns: ***benzene, a known carcinogenic***. ***The chemical was also absent in nearly 40 percent of reported fracks in Weld County*** this year, according to a Coloradoan analysis of the FracFocus database.

……

State regulations require full disclosure of fracking ingredients, with an exception for trade secrets. In February, the Colorado Oil and Gas Task Force did not pass a recommendation that would have required the dismissal of trade secret allowances. ***One-third of Larimer County's forms since 2012 claimed at least one trade secret.***

……

Chemicals make up less than 1 percent of hydraulic fracturing fluid, which is approximately 90 percent water (or anywhere from three to 7 million gallons) and 9 percent sand (or anywhere from 2 to 5 million pounds). ***Though chemicals are a small fraction of fracking fluid, "it's still toxic***," Carlson said.

……

A similar process, called "well stimulation," is used in water wells but uses non-toxic, food-grade chemicals. Some of these chemicals, such as plant-based fiber guar gum, were found in a variety of Larimer County fracks since 2012. But Carlson said the oil and gas industry ***does not often use food-grade chemicals because they are more expensive than their oil and gas industry counterparts.***

Mike Van Dyke, section chief with environmental epidemiology and occupational health at Colorado Department of Public Health and Environment, said that while there have been ***reported health concerns in Colorado and other states with significant oil and gas activity***, ***it's "very difficult" to link those concerns directly to the industry***.

……

"A lot of these chemicals that they use, ***if they get into the environment, are bad***," Carlson said. "To simplify it in my mind: ***This is a hazardous fluid.*** We cannot spill it. We cannot allow it to leak into the aquifer by a faulty casing. And anyone who is around it handling it has to treat it like it's in a chemical plant."

In Pennsylvania –

Greene County wells show 7.2 million gallons of potentially toxic fluid

Published in Herald-Standard, November 28, 2014; By Susy Kelly

7,273,480.

That's the estimated number of gallons of ***kerosene, a variety of toxic diesel fuel***, being legally used in fracking fluid in Greene County, according to chemical disclosure registry FracFocus.

Compared to Fayette County, which saw the use of 230,171 of the same chemical over three years, Greene County's figure is staggering.

Vantage alone reports using 6,645,700 of it in the 28 wells it submitted information about to FracFocus. A single well, Sandrock 1H in Gilmore Township, ***reported over half its frack fluid was kerosene***. In the majority of wells, ***a fraction of a percent of the total fluid is listed as kerosene.***

On average, non-Vantage wells in Greene County use ***2,226 gallons of CAS number 64742-47-8 per frack job, for a total of 627,780 gallons in 282 wells.***

The chemicals have left some to question the ***potential health impact.***

……

In Greene County, ***discharge to the environment has not been avoided***, as evidenced by violation notices issued to wells by the state Department of Environmental Protection (DEP).

Two wells have received notices of violation (NOV) for discharge of pollutional waters to waters of the commonwealth, seven were cited for failure to properly control or dispose of industrial or residual waste to prevent pollution to the waters, and two wells received NOVs for failure to properly store, transport, process or dispose of a residual waste. ***Those are just a fraction of all the NOVs issued in Greene County.***

……

While the EPA has outlined potential pathways for toxic flowback to find its way into groundwater, and Ken Dufalla of the Greene County chapter of the Izaak Walton League of America reports ***finding evidence of flowback in the region's waterways***, researchers have concerns for air quality as well.

……

Dr. Michael Kelly, media liaison for the Washington County-based nonprofit, said researchers began conducting a case study in 2012 to try to identify a common source for health complaints. EHP followed 27 families in the region who live in close proximity to extraction sites, Kelly said, and expects to publish the peer-reviewed data in the next few months.

"When you're dealing with chemicals, it can be ***very difficult to prove that it's a particular chemical that's causing the problem***," Kelly said.

While no single chemical can be singled out as a cause for health problems, the source can.

Kelly said, "We can't prove these symptoms are caused by fracking, but we can't prove they came from anywhere else."

At first, Kelly said, EHP advised consumers to be cautious about the drinking water. Then they began looking at the air quality surrounding fracking activities, from the exhaust of various machinery to compressor stations to water impoundments containing flowback or process water.

Kelly said the EPA and industry representatives continued to claim no pollution was coming from fracking operations, so EHP took a look at how regulatory agencies were conducting their research. When residents lodged complaints, he said, DEP would bring a 24-hour air quality monitoring canister to collect data and average the pollution emissions over that period.

……

Kelly said, "We've proven there's a public health problem. There are ***toxic-level spikes of exposure.***"

According to Kelly, the industry has kept a pace ahead of regulatory agencies, leaving the consequences related to health and the environment to be determined later.

"We're using the American people as guinea pigs ***in a huge chemical experiment.***"

……

While fracking fluid contains a host of chemicals, some of them known to be ***particularly hazardous***, the Energy Policy Act of 2005 exempts chemicals used in hydraulic fracturing from federal regulation. Colloquially, this is known as the "Halliburton Loophole."

……

Although FracFocus has been criticized for its imperfections, it remains ***the only such registry available for laypeople trying to understand the chemicals used in fracking***.

……

In some FracFocus reports from Greene County wells, ***the listed information can cause confusion***.

Five reports from EQT wells that used ***CAS number 64742-47-8***, list it as a friction reducer purchased from Halliburton, which describes the substance as "non-diesel, BTEX-free". There are 31 Consol wells that list a friction reducer ***with no CAS number, just the description*** "long chain polyacrylamide".

……

Material Safety Data Sheets (MSDS) describe a substance's toxicity and emergency procedures, and information from the MSDS supplied by Sigma Aldrich, one company that sells CAS number 64742-47-8 to frackers, says it is "***toxic to aquatic life***." It advises customers ***not to let the product enter drains***.

Online Appendix B: Additional Tables and Results

B.1 Additional Robustness Checks

Panel A: Alternative sample and beverage

	90% of weeks; Unflavored & flavored	80% of weeks; Unflavored & flavored	100% of weeks; Unflavored only
	(1)	(2)	(3)
	Ln_watersales	*Ln_watersales*	*Ln_watersales*
Disclosure	0.081**	0.072*	0.096**
	(0.033)	(0.040)	(0.041)
N	529,107	548,767	466,053
Controls	YES	YES	YES
County FE	YES	YES	YES
Year-Week FE	YES	YES	YES
Adjusted R-squared	0.983	0.976	0.983

Panel B: Alternative fixed effect structures and control group

	Alternative fixed effects			All non-fracking counties as control group
	(1)	(2)	(3)	(4)
	Ln_watersales	*Ln_watersales*	*Ln_watersales*	*Ln_watersales*
Disclosure	0.082**	0.040***	0.039***	0.100**
	(0.032)	(0.014)	(0.014)	(0.047)
N	466,053	466,053	466,053	1,386,072
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year-Week FE	NO	NO	NO	YES
Year-Month FE	YES	NO	NO	NO
State-Year-Month FE	NO	YES	NO	NO
State-Year-Week FE	NO	NO	YES	NO
Adjusted R-squared	0.984	0.988	0.986	0.986

Note: This table reports the results of additional robustness checks. Panel A presents the results from Table 2, column (2), using an alternative bottled water sample. Columns (1)–(2) report the results for bottled water sales when including stores with at least 80% or 90% of sales records during the sample period. Column (3) reports the results from Table 2, column (2) when excluding flavored bottled water. Panel B columns (1)-(3) report the results from Table 2, column (2), using alternative fixed effect structures. Panel B column (4) reports the results from Table 2, column (2) when including all non-fracking counties as the control group (including non-oil and gas counties). The fixed effect structure for each model is shown in the table. Standard errors (in parentheses) are clustered by state and reported below the coefficients. Only coefficients for the variables of interest are shown. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels (two-tailed), respectively.