Spillover Effects of State Regulated Corporate Disclosures on the Mortgage Market*

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Abstract

I investigate the spillover effects of disclosure requirements imposed by state governments on oil and gas companies operating in the state. Recently, several state governments have begun requiring companies to publicly disclose information about chemicals used in their fracking operations. The chemicals can result in land and water contamination, thereby creating uncertainty about property values near fracking operations. I hypothesize and find that the disclosure mandate reduces uncertainty about property values and subsequently increases mortgage lending activity, i.e., probability of obtaining a mortgage and loan-to-value by 2.6 and 2.2 percentage points, respectively. My analyses exploit the staggered adoption of disclosure regulations across states as well as variation in the location of properties relative to fracking wells. I conduct cross-sectional tests based on property characteristics (e.g., drinking water source, lender type) and the content of the information disclosed to further substantiate my inference that disclosures related to fracking chemicals facilitate mortgage lending activity. Finally, I find that fracking chemical disclosures decrease the variance in property prices, suggesting that a reduction in uncertainty about collateral value is the mechanism through which these disclosures affect mortgage lending. My results highlight the value of information disclosed by one sector of the economy for economic activity in different sector of the economy.

Keywords: Disclosure Regulation, Externalities, Real Effects, Mortgage Market

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1 Introduction

In most countries, a securities regulator, such as the Securities and Exchange Commission (SEC) in the U.S., is responsible for establishing corporate disclosure laws and enforcing them. The mission of a securities regulator is typically to protect investors and facilitate the smooth functioning of capital markets. Several studies examine the economic consequences of disclosure regulation, typically focusing on financial disclosures regulated by a securities regulator (see Roychowdhury et al. 2018, Leuz and Wysocki 2016 and Beyer et al. 2010 for recent reviews of the literature). However, corporate disclosure requirements imposed by other regulatory authorities (e.g., state governments, local counties, municipalities, etc.) can also affect the functioning of markets (Stiglitz 1993) but these mandated disclosures have received less attention in the literature. In this paper, I examine whether non-financial corporate disclosures provided by one sector of the economy (due to state government regulation) have externalities on an entirely different sector of the economy. Specifically, I examine whether disclosure related to the chemicals used by public and private oil and gas (O&G) firms during the extraction process has spillover effects on mortgage markets, by providing information about collateral value to mortgage lenders.

Over the past decade, technological advances have led to a significant increase in the use of hydraulic fracturing (fracking) by O&G firms to extract natural gas from shale rock in the U.S. The rapid deployment of fracking has been accompanied by concerns that the chemicals used in the fracking process contaminate land and water near fracking wells.[1] Since the disclosure of fracking chemicals is exempt from federal oversight by the Energy Policy Act of 2005, little information was publicly available until recently.[2] However, as O&G firms have moved operations into more populated areas to access oil and gas, state governments began requiring O&G firms to disclose the locations of fracking wells and the

[1]A study by the US Environmental Protection Agency (EPA) suggests that chemicals used in fracking can result in land and water contamination near the site, immediately or years after fracking operations conclude (Pinder 2013).

[2]Editorial: The Haliburton Loophole (2009, November 2). *The New York Times*, p.A28.

chemicals that are used in those wells on a public website.[3] The primary purpose of these disclosures is to provide the public with information regarding the risks of environmental hazards posed by fracking chemicals (McFeeley 2012).[4] However, these disclosures may result in an information spillover in the mortgage market. Using the staggered adoption of fracking chemical disclosure regulation ("fracking disclosures") across states and the proximity of a residential property from a fracking well within a state, I examine the spillover effects of fracking disclosures on mortgage lending activity.

I hypothesize that fracking disclosures affect mortgage lending by reducing uncertainty about the value of the housing collateral. Uncertainty about collateral value is one of the primary sources of credit risk in mortgage lending (e.g., Avery et al. 1996, Jokivuolle and Peura 2003, Harrison and Seiler 2015). Potential land and water contamination caused by fracking can significantly affect the value of the housing collateral for two reasons. First, the cost of cleaning up contamination can reduce the value of property such that the contaminated property is worth less than the outstanding balance of the mortgage on the property. In this scenario, the borrower may choose to strategically default on the loan and shift part of the loss to the lender.[5] Second, in the event of a foreclosure (unrelated to strategic default), lenders are typically obligated to pay for any clean-up costs.[6] Therefore, the lack of information about fracking chemicals used near a property can create uncertainty about collateral value of that property, hampering the ability of lenders to assess the true underlying credit risk. In this scenario, the theory of investment under uncertainty (e.g., Dixit et al. 1994) predicts that lenders may postpone

[3]There are over one million active oil and gas wells in the United States, and more than 15 million Americans now live within a mile of a fracking well (Gold R, M. T. (2013, October 25). Energy boom puts wells in America's backyards. *Wall Street Journal*, Retrieved from https://www.wsj.com/articles/energy-boom-puts-wells-in-america8217s-backyards-1382756256).

[4]Lubber, M. (2011, June 29). Investors tackle fracking and water scarcity risks. *Forbes*. Retrieved from https://www.forbes.com/sites/mindylubber/2011/06/29/investors-tackle-fracking-and-water-scarcity-risks/

[5]Using proprietary auto loan performance data, Ratnadiwakara (2018) shows that a 10% drop in collateral value corresponds to a 44% increase in default rate, suggesting that changes in collateral values have significant impact on borrowers' default decisions.

[6]Environmental regulations such as the Comprehensive Environment Response, the Compensation and Liability Act (CERCLA), the Clean Water Act (CWA) and the Resource Conservation and Recovery Act (RCRA) impose clean-up liability on the lender in the event of chemical contamination on a foreclosed property.

the decision to lend until uncertainty is resolved.[7] Fracking disclosures can inform mortgage lenders about the risk of chemical contamination for properties near fracking wells, and consequently, resolve uncertainty about the collateral value of such properties. This reduction in uncertainty can help mortgage lenders make more informed lending decisions, thereby impacting mortgage lending activity.

The manner in which mortgage lenders respond to fracking disclosures is *ex ante* unclear. Specifically, the direction of the effect fracking disclosures have on mortgage lending depends on both the quality (i.e., precision) and the content (i.e., level) of disclosures.[8] If fracking disclosures provide good news (i.e., low contamination risk from fracking), the lender's assessment of the property value increases and credit risk decreases. By contrast, if the disclosure provides bad news (i.e., high contamination risk from fracking), the lender's assessment of the property value decreases, and credit risk increases. Ignoring other effects, good (bad) news disclosures will result in an increase (decrease) in lending. However, regardless of the content of the disclosure, fracking disclosures increase the precision of the estimate of the property value, thereby reducing credit risk. This variance effect will, all else equal, result in an increase in lending for both good and bad news disclosures. The mean and variance effect work in the same (opposite) direction for good (bad) news disclosures. Thus, for good news disclosures, mortgage lending will increase. For bad news disclosures, however, mortgage lending will increase (decrease) if the variance effect (mean effect) dominates the mean effect (variance effect). The aggregate effect of fracking disclosures on mortgage lending, therefore, could either be positive

[7] Under the assumption of risk neutral investors, the theoretical literature on the investment-uncertainty relation is ambiguous. On the one hand, Dixit et al. (1994) suggest that firms reduce investments in presence of uncertainty. On the other hand, Abel (1983) shows that increase in uncertainty is positively related to investments. However, most of the empirical studies document a negative relationship between uncertainty and investments (e.g., Leahy and Whited 1995, Bloom et al. 2007). Under the assumption of risk-aversion, the theoretical models document a consistently negative relation between investment and uncertainty (e.g., Zeira 1990, Craine 1989). Similar to a nonfinancial firm that makes an investment, a lender enters into a medium to long term commitment if it decides to supply a loan. Consequently, it might be beneficial for a risk-averse lender to postpone the decision to lend in the presence of uncertainty.

[8] Kothari et al. (2009) argue that most empirical studies assume a unidirectional effect of disclosures when analyzing the capital market effects of corporate disclosures. They further note that while a unidirectional relation is expected using the quality of disclosure as the construct for disclosure, empirical measures of disclosure quality are likely influenced by the content.

or negative.

Further, it is also possible that lenders do not fully utilize fracking disclosures because of the medium through which these disclosures are disseminated (i.e., a public website). Prior research finds that some mediums disseminate information more broadly than others (e.g., Bushee et al. 2010, Blankespoor et al. 2013, Drake et al. 2015). Importantly, Christensen et al. (2017) find that SEC filings disseminate information more widely than a public website. Since fracking disclosures are disseminated through a public website rather than through SEC filings, their effect on mortgage lender's decision-making process is ultimately an empirical question.

To test my hypothesis, I utilize the introduction of fracking disclosure regulation in individual states. These regulations were adopted across several states in the U.S. at different points in time (Konschnik and Dayalu 2016), allowing me to devise tests that mitigate concerns that concurrent economic events bias my inferences. In addition, to address concerns that the timing when states change fracking disclosure rules may be endogenously related to economic activity, I utilize the differential impact of fracking disclosures on properties based on the proximity of a property to a fracking well. Specifically, I conduct property-level analysis by comparing mortgage lending activity for properties adjacent to a fracking well (less than five kilometers; henceforth, "close") to that for properties not adjacent but in the vicinity (between five and twenty kilometers; henceforth, "far") of a fracking well, before and after the fracking disclosure mandate in each state. The proximity-based identification strategy relies entirely on within-state variation in the predicted impact of fracking disclosures and as such, controls for the effect of fracking on the local economy allowing me to isolate the effect of fracking disclosure.[9] I focus on how fracking disclosure affects two measures of mortgage lending activity: probability of obtaining a mortgage loan, and loan-to-value (LTV).

Consistent with my prediction, I find that the introduction of fracking disclosure

[9]On the one hand, there is evidence that natural gas development creates jobs and generates income for residents in the short run (Weber 2012, Marchand 2012). On the other hand, recent studies report negative effects resulting from fracking such as methane leakage (Howarth et al. 2011), local air pollution (Litovitz et al. 2013), water pollution (Olmstead et al. 2013, Warner et al. 2013), and increased truck traffic (Considine et al. 2011).

laws led to a significant increase in lending activity for properties located close to fracking wells once the disclosure regulation becomes effective. In terms of economic magnitude, my difference-in-difference coefficient estimates suggest that the fracking disclosures increase the probability of obtaining a mortgage for properties close to fracking wells by 2.6 percentage points relative to properties far from fracking wells. Further, fracking disclosures increase the LTV for properties close to fracking wells by 2.2 percentage points relative to properties far from fracking wells.[10] My results are robust to controlling for property, state-year, and quarter fixed effects in all specifications. Further, by focusing on the effect of fracking disclosures on probability of obtaining a mortgage and LTV ratios, my analyses control for the changes in the primary real estate market. As such, the evidence is consistent with my hypothesis that disclosures lead to a decrease in uncertainty about collateral value in the mortgage market, thereby impacting mortgage lending activity.

To validate my results, I perform cross-sectional tests based on property and lender characteristics. First, I classify properties based on drinking water source. Fracking related contamination risks vary based on drinking water source of a property, such that properties dependent on groundwater have higher exposure to contamination risk than those dependent on piped-water. Thus, I predict and find that, after disclosures, the increase in the probability of obtaining a mortgage (LTV) is 0.6 (1.1) percentage points higher for properties that rely on groundwater compared to those that rely on piped-water. Next, I classify lenders based on their distance from the housing property and find that the increase in LTV is 0.7 percentage points higher for distant lenders relative to lenders located near the borrower. These results are consistent with the literature on soft information that suggests that geographical distance between loan officers and borrowers affects lending decisions (e.g., Bushman et al. 2017, Campbell et al. 2017, Liberti et al. 2017, Sutherland 2018).[11]

[10] The average property value for properties near fracking well is approximately \$180,000 which suggests that fracking disclosures led to an increase in loan amount by approximately \$4,000 for each mortgage loan, translating to an incremental loan balance of approximately \$460 million for close properties relative to far properties over the sample period.

[11] Liberti and Petersen (2018) provide a comprehensive review of this literature.

To analyze the effect of disclosure content (i.e., good news or bad news), I segregate groundwater properties into toxic (i.e., high contamination risk) and non-toxic (i.e., low contamination risk) based on O&G firms' fracking disclosures that provide information regarding the chemicals used in a well. From a collateral value perspective, disclosure suggesting the absence of toxic chemicals in nearby wells is good news for lenders. I expect lending to increase in non-toxic properties as the mean and variance effect work in the same direction for good news. However, lending could either increase or decrease in toxic properties since the mean and variance effect work in the opposite direction for bad news. I find that fracking disclosures result in an increase in lending for both toxic and non-toxic properties, although the increase in lending is significantly higher for non-toxic properties relative to that for toxic properties. These results suggest that the positive variance effect dominates the negative mean effect for bad news disclosures.

To establish the mechanism through which fracking disclosures affect the mortgage market, I analyze the effect of fracking disclosures on the mean and variance of sale prices of properties in close and far areas within states. I find that for close properties, the mean property price increases with good news (i.e., low contamination risk), whereas the mean property price does not show any significant change for bad news. Consistent with the idea that fracking disclosures resolve uncertainty about collateral value, I find that the variance of sale prices decreases significantly for close properties relative to far properties after fracking disclosures. Overall, these results are consistent with my hypothesis that a reduction in uncertainty about housing collateral is the mechanism through which fracking disclosures affect the mortgage market.

This paper makes three contributions. First, this paper contributes to the literature on the real effects of disclosure and disclosure quality (see Roychowdhury et al. 2018, for a review of the literature). One line of inquiry suggests that financial reporting quality helps improve investment efficiency by lowering moral hazard and adverse selection cost of the disclosing firm (e.g., Biddle and Hilary 2006, McNichols and Stubben 2008, Biddle et al. 2009, Balakrishnan et al. 2014). A stream of research examines whether accounting rules (e.g., changes in GAAP or financial reporting frequency) affect investment decisions by increasing or decreasing agency problems (e.g., Graham et al. 2011, Cho 2015, Shroff 2017, Granja 2018, Kraft et al. 2017). A third stream of literature examines whether disclosures of one firm has spillover effects on others (e.g., Bushee and Leuz 2005, Durnev and Mangen 2009, Badertscher et al. 2013, Shroff et al. 2013, Aobdia and Cheng 2018, Breuer 2018). Finally, a recent line of research examines the effect of firms' non-financial disclosures on the disclosing firm's behavior (e.g., Dyreng et al. 2016, Christensen et al. 2017, Rauter 2017). This paper adds to the literature by examining the spillover effects of non-financial disclosures on entities that are largely unrelated to the disclosing firm.

Second, this paper contributes to the literature examining the economic consequences of mandatory corporate social responsibility (CSR) disclosures. Prior research primarily focuses on either capital market effects (e.g., Grewal et al. 2017, Ioannou and Serafeim 2017) or the effects of mandatory CSR disclosures on the disclosing firm's behavior (e.g., Christensen et al. 2017, Dou and Zou 2017, Gao et al. 2016, Chen et al. 2018). The empirical evidence on spillover effects of mandatory CSR disclosures is limited. One exception is Rauter (2017) who finds that CSR disclosures by one firm can have spillover effects for non-disclosing firms in the same industry. My paper extends this line of research by providing evidence on the externalities of mandatory CSR disclosure in one sector of the economy (i.e., oil and gas industry) for economic activity in another sector of the economy (i.e., mortgage markets).

Finally, this paper contributes to the literature on the economic effects of fracking on the local economy. Muehlenbachs et al. (2015) find that homes relying on wells for drinking water have fallen in value because of drilling activity in Pennsylvania. In another study for the United Kingdom, Gibbons et al. (2016) estimate the impact of shale gas wells on housing prices. Feyrer et al. (2017) provide evidence on how income shocks propagate through local and regional economies by examining the effects of fracking on income and employment. Bartik et al. (2016) provide evidence on the local and welfare consequences of hydraulic fracturing by documenting increase in oil and gas recovery as well as deterioration in local amenities. I add to this literature by providing evidence on the economic effects of fracking disclosures. In addition, this paper sheds lights on the current policy debate regarding fracking chemical disclosures. This policy debate is focused largely on environmental consequences of these disclosures and it ignores any market-wide economic effects, which my paper examines. As such, this paper responds to the call for research by Leuz and Wysocki (2016) and Roychowdhury et al. (2018) on the market-wide or aggregate effects of disclosure regulation.

2 Institutional Setting

2.1 Hydraulic Fracturing (Fracking) Overview

Hydraulic fracturing, or "fracking", is a technique used to increase the volume of natural gas and oil that can be recovered from underground reserves. In recent years, improved horizontal drilling methods and other technological enhancements have contributed to an exponential increase in fracking activity across the United States. Hydraulic fracturing involves pumping fracturing fluid (more commonly referred to as injection fluid), which is composed of water, sand, and a small amount of chemicals, under high pressure into the rock formation to create fractures, thereby enabling any natural gas and oil trapped within the formation to escape and flow to the surface.[12] Chemicals in the fracturing fluid serve a number of purposes that enhance the productivity of water and sand. These effects include reducing the viscosity of water to allow faster pumping and to induce high pressure, enhancing natural fractures in the substrate and reducing the growth of bacteria that might interfere with the casing (Fetter 2017).

The fracking boom in the Unites States resulted in several economic and environmental impacts. Local areas facing substantial fracking activity have seen increases in population, employment, business activity, and government revenues (Weber 2012, Bartik et al. 2016). However, they also suffer from negative social, economic, and environmental consequences such as increase in crime, higher rent, adverse effect on infant health and air pollution (Currie et al. 2017, Muehlenbachs et al. 2015). The greatest environmental con-

[12]Covington & Burling LLP - Securities Advisory Report (2011, September 7). SEC asking more questions about hydraulic fracturing. Retrieved from https://www.cov.com/files/Publication/

cern comes from the toxicity of chemicals used in injection fluids (Holzman 2011). These chemicals can either migrate or be released accidentally into ground and surface water. Ideally, injection fluids that return to the surface as part of the production process must be treated before being released into surface waters, recycled, or disposed of. The treatment methods, however, are not infallible. Containment ponds can leak, contaminating surface or groundwater. Water treatment facilities may not be able to completely treat harmful chemicals, eventually leading to groundwater contamination. Storage wells, that are used to dispose of injection fluids, also run the risk of contaminating ground water (Cunningham et al. 2017).

2.2 Disclosure Regulation

Despite environmental concerns, the identity and toxicity of chemicals in injection fluids were never publicly disclosed by oil and gas companies because of a provision under the Energy Policy Act of 2005 which exempts the hydraulic fracturing process from federal oversight.[13] Public outcry and extensive media coverage eventually led to the introduction of disclosure regulations by individual states which requires oil and gas companies to disclose the name and concentration of chemical additives used in injection fluids, along with the precise location of fracking wells.

Since 2010, 28 states have introduced laws requiring disclosure of chemical additives. Out of these, 18 states have significant fracking activity (Fetter 2017). While disclosure policies remain largely the same across states, there are differences in the reporting location. Of the 18 states with significant fracking activity, six (Alabama, North Dakota, Oklahoma, Pennsylvania[14], Utah, and Texas) require operators to report information to the FracFocus registry, a web-based database created by the Groundwater Protection Council and the Interstate Oil and Gas Conservation Commission (GWPC and IOGCC

[13] StateImpact Pennsylvania (2011, December 5). Burning Question: What Would Life Be Like Without the Halliburton Loophole? Retrieved from https://stateimpact.npr.org/pennsylvania/2011/12/05/burning-question-what-would-life-be-like-without-the-halliburton-loophole/

[14] While Pennsylvania required some fracking disclosures to the state regulatory agency starting February 5, 2011, it only mandated disclosures on FracFocus starting April 16, 2012. As I am interested in public disclosures, I consider April 16, 2012 to be the beginning date for my analyses.

2015). Five states (Wyoming, Arkansas, Michigan, West Virginia, and New Mexico) require operators to report information to a state regulatory agency or commission. Six states (Montana, Louisiana, Ohio, Oklahoma, Mississippi, and Kansas) allow operators to choose their reporting location (i.e., FracFocus or the state regulatory agency), although one state (Oklahoma) notes that the state regulator will upload any information it receives to FracFocus. In one state (California), reporting to the state (rather than FracFocus) became mandatory on January 1, 2016. Figure 1 shows a sample disclosure.

3 Theory and Empirical Predictions

3.1 Conceptual Framework

In the debt contracting process, lenders have an information disadvantage, bearing downside risk with no upside potential. Therefore, assessment of credit risk becomes critically important. Institutions involved in lending, including mortgage lenders, carefully assess credit risk, which is the possibility that the borrower will fail to pay their loan obligations as scheduled. In assessing credit risk, lenders consider information across a range of factors, including financial circumstances of the borrower and the nature and value of the property serving as the loan collateral. Lenders will weigh all the factors and in some cases seek additional information in an attempt to make a more precise evaluation of credit risk (Avery et al. 1996, Jokivuolle and Peura 2003, Harrison and Seiler 2015).

Potential land and water contamination resulting from chemicals used in fracking can affect the nature and value of the housing collateral. Therefore, the contamination risk from chemicals used in fracking operations has important implications for credit risk. The contamination risk can affect lender's profitability in two ways. First, known or yet-to-be-discovered land or groundwater contamination at the property could lead to expensive investigation or cleanup obligations. The cleanup costs can result in the value of the property falling below the outstanding balance on the mortgage used to purchase the property. The borrower may choose to default if the property value has declined significantly (Ratnadiwakara 2018). Second, in the event of a foreclosure (unrelated to strategic default), lenders may incur cleanup costs due to regulatory requirements. Environmental regulations such as the Comprehensive Environment Response, the Compensation and Liability Act (CERCLA), the Clean Water Act (CWA) and the Resource Conservation and Recovery Act (RCRA), impose clean-up liability in the event of contamination.[15] In the absence of fracking disclosures, mortgage lenders are uncertain about the nature and value of the collateral, impacting the lender's ability to assess credit risk. Given the importance of fracking disclosures from a credit risk perspective, the fracking disclosures regulation is likely to have a significant effect on mortgage lending decisions. Specifically, fracking disclosures will provide contamination specific information for individual properties, thereby reducing uncertainty about the value of the housing collateral. Consequently, I predict that fracking disclosures will affect the lender's decision to lend, impacting mortgage lending activity.

My prediction is based on the theory of investment under uncertainty. Similar to a nonfinancial firm that makes an investment, a mortgage lender also enters a long term commitment if it decides to supply a loan. The predictions under the theoretical literature depend on investors' risk preferences. Under the assumption of risk aversion, the investment-uncertainty relationship is consistently negative (e.g., Craine 1989, Zeira 1990). However, the theoretical literature on the effects of uncertainty on investments, based on the assumption of risk neutrality, is ambiguous. On the one hand, Hartman (1972) and Abel (1983) found that in the presence of convex costs of adjustment, mean-preserving increases in price uncertainty raise investment of a competitive firm as long as the profit function is convex in prices. On the other hand, Dixit et al. (1994) show that increase in uncertainty lowers investment when investments are irreversible. Moreover, most empirical studies find a negative relation between uncertainty and investment (e.g., Leahy and Whited 1995, Bloom et al. 2007). Given that risk aversion is an important characteristic of lending behavior, the theory of investment under uncertainty suggests that

[15]The Lexis Practice Advisor Journal (2017). Lender Liability Under Environmental Laws in Real Estate Transactions. Retrieved from https://www.lexisnexis.com/lexis-practice-advisor/the-journal/b/lpa/archive/2017/02/09/lender-liability-under-environmental-laws-in-real-estate-transactions.aspx

lenders may postpone the decision to lend in the presence of uncertainty about collateral value.[16] Fracking disclosures may help resolve this uncertainty about housing collateral, thereby impacting the mortgage market.

3.2 Hypothesis Development

The manner in which mortgage lenders respond to fracking disclosures is *ex ante* ambiguous because it depends on (i) the level and precision of the lender's estimates of property values, and (ii) the information dissemination channel.

The theory of investment under uncertainty suggests that fracking disclosures will result in an increase in mortgage lending as lenders can estimate the value of collateral more precisely. However, in the context of capital market effects of disclosures, Kothari et al. (2009) note that while a unidirectional link is expected using the quality (i.e., precision) of disclosure, the content (i.e., level) of disclosures is likely to influence the quality. Consistent with this idea, I argue that the direction of the effect fracking disclosures have on mortgage lending depends on both the quality and the content of disclosures. Specifically, if fracking disclosures provide good news (i.e., low contamination risk from fracking), then the lender's assessment of the property value increases and credit risk decreases, while if fracking disclosures provide bad news (i.e., high contamination risk from fracking), then the lender's assessment of the property value decreases and credit risk increases. Ignoring other effects, good (bad) news disclosures will result in an increase (decrease) in lending. However, regardless of the nature of the disclosure, fracking disclosures increase the precision of the estimate of the property value, thereby reducing credit risk. This variance effect will, all else equal, result in an increase in lending for both good and bad news disclosures. The mean and variance effect work in the same (opposite) direction for

[16]Risk aversion is an important characteristic of lending behavior. Froot et al. (1993) and Froot and Stein (1998) show that if a bank faces a strictly increasing marginal cost of funds (e.g., due to informational asymmetries), then its final wealth is a strictly concave function of the amount of internal funds available for intermittent investment opportunities. As a result, the bank makes decisions that affect the amount of available internal funds in an effectively risk-averse manner. Basel capital adequacy rules force banks to avoid investments with possibly harsh detrimental consequences for its equity. Pausch and Welzel (2002) show that a minimum-capital constraint makes a risk-neutral bank's objective function strictly concave in wealth, so that the bank becomes effectively risk-averse.

good (bad) news disclosures. Thus, the overall effect on the mortgage market depends on whether the aggregate assessment of credit risk associated with the collateral is higher or lower than expected.

These arguments assume that lenders are aware of and use these mandated disclosures. It is possible that lenders do not utilize fracking disclosures as they are disclosed through a public website and not through a conventional dissemination channel, such as corporate websites, press releases, social media and financial reports. Prior research finds that some mediums disseminate information more broadly than others (e.g., Bushee et al. 2010, Blankespoor et al. 2013, Drake et al. 2015). Consistent with this idea, Christensen et al. (2017) find that SEC filings disseminate information more widely than a public website medium. Since fracking disclosures are disseminated through a public website rather than through SEC filings, they may not have any effect on mortgage lender's decision-making process.

Therefore, the effect of fracking disclosures on the mortgage market is ultimately an empirical question.

4 Empirical Methodology and Evidence

4.1 Identification Strategy

The staggered adoption of disclosure regulation across states provides an interesting quasi-natural experiment setting, however, there are some endogeneity concerns. On the one hand, states differ in terms of economic performance, employment, and other dimensions, making comparison across states difficult. It is also possible that the disclosure dates are not exogenous and that omitted state-level factors which impact mortgage lending could also drive the disclosure regulation timelines. On the other hand, mortgage markets function differently from stock markets. Some of the states (Colorado, North Dakota, Pennsylvania, Utah, and Texas) implemented these disclosure regulations in the same year but in different months. From a mortgage market perspective, it can be argued that the difference across months does not qualify as a true staggered adoption setting as mortgage markets may take longer to adjust to any new information. In order to address these endogeneity concerns, I compare mortgage lending activity within states. Since the disclosure regulation happens simultaneously in all counties in a specific state, I need to identify an area that is less likely to be impacted by these disclosures and can serve as a control group.

To establish causality, I follow a strategy similar to that employed by Linden and Rockoff (2008) and Muehlenbachs et al. (2015).[17] I utilize the variation in impact of disclosure regulation based on the property's proximity to a fracking well. Figure 2 is useful in describing my identification strategy. I define *vicinity* as the area enclosed by the circle with a radius r_1 drawn with the well as the center. *Adjacent* area is defined as a subset of *vicinity* with a radius r_2 where $r_2 < r_1$. In the figure, the combined area of A and B (mesh pattern) denotes *vicinity* and area A (shaded region) denotes *adjacent* area. Area C is an area which is beyond the *vicinity* ($> r_1$). I define area A as the *close* or treatment area and area B as the *far* or control area for my analysis.

The identification strategy relies on the fact that both area A and area B are within the vicinity of a well and, on average, would experience similar economic outcomes. These outcomes can either be macro in nature, such as a housing bubble, recession, and other regional economic impacts, or specific effects resulting from abundant fracking activity in the area, such as increased local employment, traffic congestion, etc. (e.g., Weber 2012, Marchand 2012, Howarth et al. 2011, Litovitz et al. 2013, Olmstead et al. 2013, Warner et al. 2013, Considine et al. 2011, Muehlenbachs et al. 2015, Feyrer et al. 2017). This strategy assumes that the only difference in mortgage lending activity in these two areas would arise from disclosure regulations because the ill effects of fracking chemicals are applicable only to adjacent properties.

There is limited guidance in prior empirical literature about how near a household

[17] Linden and Rockoff (2008) estimate the impact of crime risk on property values. Using sex offenders' precise location, they compare house sales within very small areas in which housing stock is more homogenous than in normal aggregate comparisons. Muehlenbachs et al. (2015) identify the impact of shale gas development on housing prices using similar strategy as Linden and Rockoff (2008)

must be to a fracking well to be significantly impacted by fracking chemicals. Muehlenbachs et al. (2015) use multiple distance thresholds (1 kilometer (Km), 1.5 Km and 2 Km) to define adjacency. Hill et al. (2013) show the effect of shale gas development on infant health using 2.5 Km and 3.5 Km as primary distances of interest. Farah (2017) suggest that areas within 0-5 Km experience both direct and indirect effects of fracking. Therefore, I rely on scientific studies documenting the effects of fracking contamination in close proximity of fracking areas (e.g., Hildenbrand et al. 2016, Epstein 2017) and set r_1 as 20 Km and r_2 as 5 Km.[18]

4.2 Sample and Data

I obtain disclosure regulation implementation dates for respective states from Konschnik and Dayalu (2016). Table 1 provides disclosure timeline for individual states. The table shows that reporting locations vary across states. For my analysis, I require that all chemical disclosures for a state be available publicly on FracFocus online registry. Therefore, I focus on five states that require operators to report information to the FracFocus registry.[19] Following Fetter (2017), I also include FracFocus reports from Oklahoma and California.[20] My final sample of states consists of California, Colorado, North Dakota, Oklahoma, Pennsylvania, Texas, and Utah.

Next, I obtain disclosure data from the FracFocus database. For each well, the database has details including location (county, state, latitude, longitude), name of operator, fracture date, depth, water volume, and chemical additives. For each chemical, I can also see the purpose, name of the supplier, maximum concentration in the injection fluid

[18] In untabulated results, I vary these thresholds and find similar results.

[19] FracFocus is also the reporting registry for wells fracked in Alabama, but there were very few wells in that state during the analysis period (126) and even fewer wells that meet the criteria for usable observations. Thus, following Fetter (2017), I exclude Alabama from the analysis.

[20] As mentioned earlier, while operators in Oklahoma can choose whether to report to FracFocus or to the state, the state's disclosure law indicates that the regulatory agency will upload to FracFocus all information it receives. California used FracFocus as an alternative reporting site prior to January 1, 2016 and allowed operators to report to either FracFocus or the California state registry. The state regulatory agency in California provides comparable and publicly accessible data similar to that on FracFocus. My current sample ends at December 2015, making FracFocus data sufficient for any analysis for the state of California. For my current analysis, I do not download any data from the state regulating agency.

and an identification number (Chemical Abstracts Service (CAS) number).[21] I download FracFocus data from February 2012 to December 2015 to ensure that the sample has at least two years of origination data before disclosure and two years of origination data after disclosure for each state. To test my main hypothesis, it is important that the data has sufficient and correct location information. I drop observations with missing latitude or longitude values. I also delete observations where the listed state name does not match the numerical state code. The resulting dataset has 108,608 distinct wells.

I obtain mortgage lending data for my sample states (California, Colorado, North Dakota, Oklahoma, Pennsylvania, Utah, and Texas) from CoreLogic, a national real estate data provider. I gather details including sale date, sale amount, precise address (including latitude and longitude), and mortgage amount for all transactions. I begin with transaction records of all properties sold in these states between January 2005 and December 2015. Observations consisting of the following types of transactions are excluded from the sample: (1) non-arm's length transactions (Gau and Wang 1990); (2) sale without a transaction date; (3) sale with missing or erroneous values for latitude and longitude; (4) sale where the mortgage amount was greater than the sale amount, and, (5) duplicate sale. For my research design, I require that the property be sold at least once before the disclosure and at least once after the disclosure (Muehlenbachs et al. 2015). I also restrict my sample to properties with a sale value of less than or equal to one million U.S. dollars to mitigate the influence of extreme outliers.[22]

While I compare properties in the vicinity of a well, it would still be problematic to establish causal evidence if property characteristics vary within these small areas in ways that are unobservable to the researcher. For example, it is possible that wells are located in areas where housing quality is low for some reason, unrelated to the disclosures. In order to address this concern, I focus on the set of properties that were sold before and after the disclosures. In order to conduct this test, I create a subsample of properties that

[21] A CAS Registry Number ("CASRN" or "CAS") is a unique numerical identifier assigned by the Chemical Abstracts Service (CAS) to every chemical substance described in the open scientific literature.

[22] The results are quantitatively similar when I winsorize (and do not truncate) the sale price at 1% and 99%.

were sold more than once, with at least one sale before disclosure and at least one sale after disclosure. In other words, I compare the same properties before and after disclosure.

To classify a property as either treatment or control, I merge the fracking dataset with the sample of properties. Specifically, I utilize the longitude and latitude information from both datasets to calculate distance of a property from a fracking well. Any property within 5 Km of a fracking well is defined as treatment or close, and any property beyond 5 Km but within 20 Km of a fracking well is defined as control or far.[23] The final dataset has 916,889 property transactions.

I conduct most of my analyses at the property level.[24] However, I do provide aggregate level results as a robustness for my main results. Specifically, to assess the effect of fracking disclosures on the mortgage market, I focus on two measures of mortgage lending activity: probability of obtaining a mortgage loan, and loan-to-value (LTV) ratio at the time of mortgage origination.[25]

4.3 Empirical Model and Results

I estimate the following property level regression:

$$y_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t} \tag{1}$$

The dependent variable is either an indicator variable equal to one if the sale of

[23]For research design purposes, it would have been ideal if I had fracking well location data before as well as after disclosure regulations were implemented. In absence of this information, I assume that the property that was close to (far from) a fracking well in post-disclosure period was also close to (far from) a well in the pre-disclosure period. Therefore, my classification of properties as close or far does not change over time.

[24]The unit of analysis can either be at the aggregate level or at an individual property level. Stoker (2008) notes that understanding economic aggregates is essential for understanding economic policy because of substantial individual or household heterogeneity. However, he further notes that individual heterogeneity is pervasive with substantial empirical evidence and should be considered to interpret economic aggregates. While this paper focuses on overall mortgage lending in local markets, household level data provides an opportunity to understand the change in lending at a lower level of detail.

[25]To test the effect of fracking disclosures on other loan terms (e.g., interest rates, mortgage term), I would need to match the CoreLogic real estate dataset with Loan-Level Marketing Analytics (LLMA) dataset (also provided by CoreLogic). While the LLMA dataset is available, the contract with CoreLogic prohibits us from merging the two datasets. Therefore, although desirable, I cannot provide any evidence on other loan terms.

property i at time t was financed by a mortgage, zero otherwise ($Loan_{i,t}$) or dollar value of loan scaled by dollar value of sales transaction for sale of property i at time t ($LTV_{i,t}$). $Post_{i,t}$ is an indicator variable equal to one beginning in the year-month in which disclosure regulation becomes effective in an individual state. $Close_i$ represents Area A in Figure 2. In addition to state by year fixed effects ($\delta_{s,t}$) and quarter fixed effects (q_t), I also include property fixed effects (γ_i) in this specification to control for structural differences between different properties. The independent variable $Close_i$ is not included in equation (2) as it is subsumed by the presence of property fixed effects. I adjust standard errors for within group clusters at the property level and at the year-month level.[26]

The coefficient of interest is β_2 which measures the change in the mortgage lending difference between close and far areas. $\beta_2 > 0$ would mean that disclosure regulations had a positive impact on mortgage lending activity in close areas (relative to far areas). $\beta_2 < 0$, in contrast, would mean that disclosures led to a decrease in mortgage lending activity in close areas (relative to far areas).

Table 2 provides descriptive statistics for the complete sample and sub-samples. The average property price before disclosures is \$181,680 (i.e., $e^{12.11}$) and \$198,780 (i.e., $e^{12.20}$) after disclosures. In terms of the variables of interest, the descriptive statistics suggest that probability of obtaining a mortgage ($Loan$) increased from 0.84 to 0.89 for the close sub sample. It also shows that loan-to-value (LTV) increased from 0.68 to 0.76 after disclosures.

Figure 3a shows the number of mortgages originated in my sample states from 2005 to 2015. The time trend suggests that the lack of information about fracking chemicals adversely impacted the number of loans in my sample states. The graph also shows that there was a surge in mortgage lending activity following fracking disclosures. I also look at the dollar volume of mortgages in Figure 3b. The effect is evident even for the dollar volume of mortgages.

Table 3 presents the results for property-level regression estimation in equation (1) for

[26] I do not cluster by state because the number of state clusters is only seven which would otherwise inflate statistical significance (Petersen 2009).

the estimated average effect of fracking disclosures on mortgage lending activity. Column (1) shows the results for probability of obtaining a mortgage (*Loan*). The coefficient on $Close \times Post$ (β_2) is positive and significant (coefficient: 0.026; t-statistic: 14.92). The estimated coefficient implies that probability of obtaining a mortgage for close properties increased by 2.6 percentage points once fracking disclosure regulation became effective. Column (2) provides results for LTV. The coefficient is positive and significant (coefficient: 0.022; t-statistic: 14.28) suggesting that borrowers are able to finance a greater percentage of the property value after disclosures. The average property value for properties near a fracking well is approximately \$180,000, which suggests that fracking disclosures led to an increase in loan amount by approximately \$4,000 for each mortgage loan, and approximately \$460 million over the sample period in aggregate terms for close properties relative to far properties. My results are in line with the notion that mortgage lenders use the newly available fracking disclosure information to analyze credit risk associated with the collateral, thereby impacting the mortgage lending activity.

4.4 Robustness

In order to check the robustness of my results, I limit my sample period to four years for each sample state, with two years before disclosures defined as the pre-period and two years after disclosures defined as the post-period. I also impose a similar restriction in my main tests where I require that the property be sold at least once before disclosure and at least once after disclosure. Table 4 shows that the coefficient on the $Close \times Post$ variable is positive and significant for both dependent variables. The results are similar to my main specification, confirming my hypothesis that these disclosures led to a decrease in uncertainty about collateral in the mortgage market and led to an increase in overall mortgage lending.

While I conduct my analysis on property-level data, I provide evidence on aggregate level mortgage lending in Table 5. For aggregate level analysis, I estimate following difference-in-difference design where I compare mortgage lending activity in close and far areas, before and after the disclosure.

$$y_{i,t} = \alpha + \beta_1 Close_i + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} + \delta_{i,t} + q_t + \epsilon_{i,t} \tag{2}$$

I consider two dependent variables for equation (2). One is the number of mortgages originated in state i in year-month t divided by the number of real estate sales in the same period in state i. The other is the dollar volume of mortgages originated in state i in year-month t divided by the dollar value of real estate sales in state i for the same period. Other variables are defined as before. I include state by year fixed effects ($\delta_{i,t}$) to control for time-varying unobservables at the state level. I also include a temporal fixed effect indicating the quarter (q_t). I cluster standard errors by year-quarter.

Table 5 Column (1) shows the results for aggregate regression estimation using number of loans scaled by real estate sales ($NLoan$) as a dependent variable. The coefficient of $Post$ indicator is positive and significant (coefficient: 0.050; t-statistic: 2.28), which implies that disclosures had a positive impact for both close and far areas. The coefficient of interest is the coefficient on the interaction term ($Close \times Post$). It is positive and significant (coefficient: 0.050; t-statistic: 9.31), suggesting an increase in the number of mortgage originations in close areas after fracking disclosures. Table 5 Column (2) shows the result for dollar volume of loans ($DLoan$). I find that dollar volume of mortgages also increased in the post-disclosure period since the coefficient of $Post$ is positive and significant (coefficient: 0.033; t-statistic: 1.79). Moreover, β_3 is positive and significant (coefficient: 0.036; t-statistic: 5.99), which suggests that the increase in dollar volume of mortgages was higher for the close area compared to the far area.

5 Cross-sectional Analyses

5.1 Drinking Water Source

To provide further evidence on the effect of disclosures on mortgage lending activity, I classify close properties based on their drinking water source as either groundwater dependent or piped-water dependent. Groundwater contamination is one of the biggest environmental risks associated with fracking. Consistent with this idea, Muehlenbachs et al. (2015) show that properties dependent on groundwater as a drinking water source experience a large negative impact on property value. Thus, it is likely that lenders would consider groundwater dependent properties riskier compared to piped-water dependent properties. If so, I expect the effect of collateral value uncertainty to be greater for groundwater dependent properties relative to piped-water dependent properties before disclosures. Therefore, I predict that after fracking disclosures, mortgage lending activity should increase more in groundwater dependent properties relative to piped-water dependent properties.

To classify a property as groundwater or piped-water dependent, I utilize data on Public Water Service Areas (PWSAs) similar to Muehlenbachs et al. (2015). I obtain the geographic information system (GIS) boundaries of the public water suppliers' service areas in all states (except Colorado).[27] The data provides boundaries of public water supply areas (i.e. all the properties within a boundary use public water or piped water). Figure 4a shows a sample PWSA for the state of California. Following Muehlenbachs et al. (2012), I assume that any property outside these boundaries is groundwater dependent.

Using latitude and longitude data from CoreLogic and ArcGIS software, I overlay residential properties for each state on the PWSA. Figure 4b shows the map of properties over the PWSA for the state of California. The blue shaded part denotes the area where water is supplied by a public water service system and the red dot represents a specific residential property. I create similar maps for all other states (except Colorado). Using ArcGIS software, I code my properties as either groundwater dependent or piped-water dependent to conduct my analysis.

In order to test the differential impact of water source on mortgage lending activity,

[27] The Public Water Service Areas (PWSAs) are publicly available at individual state websites except for Colorado.

I estimate the following triple difference regression:

$$\begin{aligned} y_{i,t} &= \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} \\ &+ \beta_3 Close_i \times GW_i \times Post_{i,t} \\ &+ \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

GW_i is an indicator variable equal to one if the property i is groundwater dependent, zero if property i is piped-water dependent. Other variables are defined as before.

I predict a positive and significant coefficient on $Close \times GW \times Post$, i.e., groundwater properties will experience greater increase in mortgage lending after disclosure regulation compared to piped-water properties. Table 6 shows these results.[28] As predicted, the coefficient on $Close \times GW \times Post$ is positive and significant for both of my dependent variables (*Loan* coefficient: 0.006; t-statistic: 2.58, *LTV* coefficient: 0.011; t-statistics: 4.81). In terms of economic magnitude, the results show that the increase in the probability of obtaining a mortgage is 0.6 percentage points higher for properties that rely on groundwater compared to those that rely on piped-water. Similarly, the increase in LTV is 1.1 percentage points higher for groundwater properties relative to piped-water properties. Table 6 also shows that the coefficient on $Close \times Post$ is significant and positive (*Loan* coefficient: 0.024; t-statistic: 14.14, *LTV* coefficient: 0.019; t-statistics: 12.64), suggesting that piped-water properties also observe a significant increase in mortgage lending activity. This result shows that while groundwater contamination is a big concern for lenders, other collateral value concerns (for example, air pollution in the neighborhood) still play an important role in a mortgage lender's decision to lend.

I run an F-test of joint significance of the coefficients on the interaction terms (i.e., $Close \times Post$ + $Close \times GW \times Post$) and find that for the full sample, they are jointly significant. In terms of economic magnitudes, the summation of the two coefficients implies a statistically significant increase of 3 percentage points in the probability of obtaining a mortgage (p-value: 0.00) as well as in the LTV (p-value: 0.00) for groundwater dependent

[28] The number of observations is smaller (757,368) compared to the main sample (916,889) because the data for Colorado PWSA is not available.

homes. Taken together, the results in Table 6 suggest that fracking disclosures inform mortgage lenders about collateral value, thereby impacting mortgage lending activity.

5.2 Lender Type

Based on the theoretical predictions on the challenge of transmitting some types of information (i.e., soft information), a branch of the traditional banking literature shows that geographical distance affects lending decisions (e.g., Bushman et al. 2017, Campbell et al. 2017, Liberti et al. 2017, Sutherland 2018).[29]. The literature has interpreted this finding largely in terms of the difficulty of transmitting soft information. Berger et al. (2005) provide evidence that small banks are better able to collect and act on soft information compared to large banks. In particular, large banks are less willing to lend to informationally *difficult* credits, such as firms with no financial records.

If transmission of soft information depends on the geographic distance between the lender and the borrower, I expect, in the absence of disclosures, distant or *global* lenders to face higher uncertainty regarding collateral values relative to close or *local* lenders. To test this prediction, I classify the lenders as global or local based on their distance from the housing property. Using lender and property zip codes from the CoreLogic dataset, I classify property level transactions as global if the distance between the lender and the property is equal to or greater than 25 miles, and as local if the distance between the lender and the property is less than 25 miles (see Berger et al. 2005).[30]

I estimate equation (1) for local and global subsamples using LTV as the dependent variable. Table 7 shows the results of this regression.[31] Column (1) shows the results for the local subsample. The coefficient on $Close \times Post$ is not significant. However, the corresponding result in column (2) for the global subsample is positive and significant. The magnitude of the coefficient suggests that fracking disclosures result in a 0.2 percentage

[29] Liberti and Petersen (2018) provide a comprehensive review of this literature.

[30] Berger et al. (2005) show that mean distance between lender and borrower is approximately 26 miles.

[31] The number of observations is smaller (665,374) because the data is limited to property transactions with a mortgage loan. I also exclude those observations where zip code for mortgage lender was unavailable.

points increase in LTV for close properties relative to far properties when the loans were originated by global lenders.

To test the statistical significance of the difference between global and local lenders, I estimate the following triple difference regression:

$$\begin{aligned} LTV_{i,t} = \alpha + \beta_1 Close_i \times Local_{i,t} + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} \\ + \beta_4 Close_i \times Local_{i,t} \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

$Local_{i,t}$ is an indicator variable equal to one if the distance between mortgage lender and property i is less than 25 miles for sale at time t, zero otherwise. Other variables are defined as before.

Table 7 Column (3) shows the results for the entire sample. The coefficient on $Close \times Post$ is significant and positive (coefficient: 0.007; t-statistic: 8.03), which suggests that fracking disclosures led to an increase in mortgage lending activity for global lenders. The coefficient on $Close \times Local \times Post$, on the other hand, is significant and negative (coefficient: -0.017; t-statistic: -7.79), suggesting that the increase in LTV for local lenders is significantly lower relative to global lenders. These results provide evidence consistent with the expectation that global lenders face higher uncertainty about collateral value, *ex-ante*. Fracking disclosures help resolve this uncertainty, which impacts mortgage lending decisions by global lenders.

5.3 Good News vs. Bad News

The disclosures could either be good or bad depending upon the risk of contamination. On the one hand, the risk of contamination is high if a fracking well close to a property uses one or more toxic chemicals. From a collateral value perspective, high environmental risk is bad news for lenders. On the other hand, the risk is low if a fracking well close to a property does not use any toxic chemicals. Low environmental risk is good news for lenders. To test the differential effect of good versus bad news disclosures, I segregate groundwater properties into toxic and non-toxic based on the chemical used in an adjacent well. Toxic properties (i.e., bad) are those set of properties that are close to a well that uses one or more toxic chemicals. Lenders are therefore subjected to environmental contamination risk if they lend to these properties. Non-toxic properties (i.e., good) are those set of properties that are close to a fracking well (or wells) that do not use toxic chemicals. Consistent with my hypothesis, I expect lending to increase in non-toxic properties since the mean and variance effects work in the same direction for good news. However, lending could either increase or decrease in toxic properties since the mean and variance effects work in opposite directions for bad news.

To classify a property as toxic or non-toxic, I use chemicals data from fracfocus.org. I start with a chemical's CAS number to identify whether or not it is considered toxic under regulatory classifications. I utilize four regulatory classifications: (1) The United States Environmental Protection Agency's (EPA) identified 1,173 chemicals associated with hydraulic fracturing fluids, flowback, or produced water (Yost et al. 2016). Traditional toxicity estimates were available for 147 chemicals. Based on EPA's toxicity classification for these 147 chemicals, I classify 43 chemicals as toxic. The EPA released a software (TOPKAT) based toxicity ranking for 417 chemicals. This list ranks chemicals in the order of their toxicity. I use top 50 chemicals from this list and define them as toxic for the purpose of my classification; (2) I use the list of 65 (73 including compounds) chemicals that are regulated as primary contaminants under the Safe Drinking Water Act (SDWA); (3) I also use the list of 126 chemicals that are considered as Priority Toxic Pollutants under the Clean Water Act (CWA); (4) Similar to Fetter (2017), I use a final group that includes chemicals listed in the USEPA's Risk-Screening Environmental Indicators (RSEI) database (USEPA 2012b) as having relatively high risk value for chronic human health effects. I classify chemicals as toxic if they have an RSEI score of at least 200 (Fetter 2017).

I create a binary measure of toxicity for each well; this measure classifies a well to be toxic if it contains at least one of the toxic chemicals identified from the above four sources.

To test the effect of good news versus bad news, I estimate following regression:

$$
\begin{aligned}
y_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \beta_3 Close_i \times GW_i \times Post_{i,t} \\
+ \beta_4 Close_i \times GW_i \times Toxic_i \times Post_{i,t} + \delta_{i,t} + \gamma_i + q_t + \epsilon_{i,t}
\end{aligned} \tag{5}
$$

$Toxic_i$ is an indicator variable equal to one if property i is close to at least one toxic well, zero if property i is not close to any toxic well. Other variables are defined as before.

Table 8 shows these results. The coefficient on $Close \times GW \times Post$ is 0.037 for *Loan*, which suggests that the probability of obtaining a mortgage increased by 3.7 percentage points for non-toxic properties when the disclosed news is good. The coefficient in column (2) suggests that *LTV* increased by 3 percentage points for non-toxic properties. I run an F-test of joint significance of the coefficients to estimate the total effects for non-toxic properties and find that they are jointly significant for both *Loan* (p-value: 0.00) and *LTV* (p-value: 0.00).

The coefficient on $Close \times GW \times Toxic \times Post$ in column (1) is significant and negative. It suggests that the probability of obtaining a mortgage loan for toxic properties was 1.3 percentage points lower compared to non-toxic properties. The results for column (2) is in the same direction as the column (1) but not statistically significant. The F-statisitc suggests that the total effects for *LTV* (p-value: 0.00) and *Loan* (p-value: 0.00) are significant and positive. These results show the effect of bad news disclosures.

Overall, I find that fracking disclosures result in an increase in lending for both toxic and non-toxic properties, although the increase in lending is significantly higher for non-toxic properties relative to that for toxic properties. These results suggest that the positive variance effect dominates the negative mean effect for bad news disclosures.

6 Mechanism

6.1 Collateral Value

Given that my results indicate that fracking disclosures influence the mortgage market, I next explore one of the possible mechanisms, the collateral value. I assess the effects of fracking disclosures on collateral uncertainty by comparing the level and the variance of property prices for close properties with far properties, before and after fracking disclosure regulation. If fracking disclosures affect the level and the variance of sale prices, and lenders incorporate these changes in their decision to lend, then fracking disclosures will have an impact on the mortgage lending activity.

I begin my analysis by examining the effect of fracking disclosures on the precision of sale prices. If housing collateral is the mechanism through which fracking disclosures affect mortgage lending then I expect the precision of sale prices to improve for close properties relative to far properties, after the disclosure compared to before. To estimate the precision of sale prices, I calculate the variance of sale prices in individual states in a specific year-month for close and far areas.[32] I estimate the following regression:

$$Var(Sale)_{i,t} = \alpha + \beta_1 Close_i + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} + q_t + \epsilon_{i,t} \tag{6}$$

The dependent variable is the variance of sale prices for properties that are sold in state i at time t ($Var(Sale)_{i,t}$). Other variables are defined as before.

Table 9 Column (1) provides the result of the regression estimation. The coefficient on $Close \times Post$ is negative and significant (coefficient: -0.029; t-statistic: -2.80) which implies that the introduction of fracking disclosures reduced the variance of sale prices for close properties relative to far properties.

[32] My sample restrictions require that a property needs to be sold at least once before disclosures and at least once after disclosures. Therefore, property-level estimation of variance would result in a decrease in number of observations, thereby reducing the power of my tests. Specifically, the sample will be limited to those properties that have been sold at least three times before disclosures and at least three times after disclosures. The estimation of variance at state and year-month level utilizes information content of my entire sample. In untabulated results, I estimate variance at a property level for the limited sample (4,992 observations) and find similar results.

To estimate the difference in variance between toxic and non-toxic properties, I calculate the variance of sale prices at the level of state, year-month, close, groundwater dependent and toxic classification. The regression is as follows:

$$
\begin{aligned}
Var(Sale)_{i,t} = \alpha &+ \beta_1 Close_i + \beta_2 Close_i \times GW_i + \beta_3 Close_i \times GW_i \times Toxic_i \\
&+ \beta_4 Post_{i,t} + \beta_4 Close_i \times Post_{i,t} + \beta_5 Close_i \times GW_i \times Post_{i,t} \\
&+ \beta_3 Close_i \times GW_i \times Toxic_i \times Post_{i,t} + q_t + \epsilon_{i,t}
\end{aligned} \tag{7}
$$

Table 9 Column (2) shows the results for variance calculated for toxic and non-toxic properties within close groundwater dependent properties. It shows that there is no discernible difference between toxic and non-toxic properties. In other words, the decrease in variance is statistically similar for both good and bad news properties.

Overall, these results suggest that fracking disclosures improved the precision of property prices, thereby impacting the mortgage lender's decision to lend.

Next, I assess the effect of fracking disclosures on the level of sale prices. Given that the mean effect is directional, I estimate the following sales price regression:

$$
\begin{aligned}
log(Sale)_{i,t} = \alpha &+ \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} \\
&+ \beta_3 Close_i \times GW_i \times Post_{i,t} \\
&+ Close_i \times GW_i \times Toxic_i \times Post_{i,t} \\
&+ \delta_{i,t} + \gamma_i + q_t + \epsilon_{i,t}
\end{aligned} \tag{8}
$$

The dependent variable is natural logarithm of sale price for sale of property i at time t. Other variables are defined as before.

I divide my sample into groundwater dependent toxic and non-toxic properties to estimate the mean effect for bad news and good news, respectively. Table 10 shows that the average sale price increases for non-toxic properties (coefficient: 0.027; t-statistic: 4.23). The negative coefficient on $Close \times GW \times Toxic \times Post$ suggests that the average price for toxic properties is significantly lower (coefficient: -0.022; t-statistic: -2.84) relative to non-toxic properties after fracking disclosures. These results are consistent with the idea that the introduction of fracking disclosures results in a shift in the level of sale prices.

Overall, the results in this section suggest that changes in the level and the precision of housing collateral value is one potential mechanism through which fracking disclosures affect the mortgage market. However, it is important to note that these findings do not preclude the possibility that other mechanisms are also at work.

6.2 Alternative Mechanisms

One potential alternative mechanism for the increase in mortgage lending activity is that it is driven by the secondary mortgage market. Ninety percent of America's residential mortgage loans are sold into the secondary mortgage market.[33] Currently the Federal Housing Administration (FHA) insures mortgages which are sold into the secondary mortgage market to such entities as Fannie Mae and Freddie Mac. Section 4150.2 of the FHA's Valuation Analysis for *Single Family One-to Four- Unit Dwellings* issues site requirements for FHA-insured mortgages, which are to be considered by the lender's property appraiser before the property valuation process can begin.[34] A review of the site analysis guidelines reveals numerous circumstances under which an appraiser would caution or even recommend rejection of a mortgage of the underlying property if there is an observed or anticipated danger to the health or safety of the occupants (Radow 2013).

It is possible that, in the absence of fracking disclosures, residential properties close to a fracking well were unable to qualify for FHA insurance. As a result, the sale of mortgages in the secondary market was impacted as investors considered these mortgages too risky. Therefore, the *ex-ante* decrease in mortgage lending activity resulted from the effect of fracking contamination risk on the insurance eligibility for secondary mortgage market purposes. The introduction of fracking disclosures provides relevant information about the potential danger to health and safety of the occupants, thereby impacting the

[33] Congress of the United States Congressional Budget Office. (2010, December). Fannie Mae, Freddie Mac, and the federal role in the secondary mortgage market. Retrieved from http://www.cbo.gov/sites/default/files/cbofiles/ftpdocs/120xx/doc12032/12-23-fanniefreddie.pdf

[34] U.S. Department of Housing and Urban Development. Valuation Analysis for Single Family One- to Four- Unit Dwellings Handbook, Section 4150.2. Retrieved from https://www.hud.gov/program_offices/administration/hudclips/handbooks/hsgh/4150.2

insurance eligibility of properties in close proximity of fracking wells. The increase in lending then could have been a result of the insurance channel instead of the collateral channel. This mechanism, however, is not empirically testable due to the unavailability of insurance data.

7 Conclusion

Mandatory corporate disclosures are increasingly used by policymakers to decrease information asymmetry and uncertainty between firm and its stakeholders, and to improve the efficiency of capital markets. Many empirical studies in accounting literature provide evidence on the capital market and real effects of mandatory firm disclosures. However, most of the empirical studies focus on financial or non-financial disclosures mandated by the SEC (or other securities market regulators). The corporate disclosure regulations by non-SEC regulators can also have material implications for the economy. In this paper, I examine the spillover effects of state mandated corporate disclosures, which require oil and gas firms to disclose the chemicals used in their fracking operations, on the mortgage market. I exploit plausibly exogenous variation in adoption of fracking disclosures across different states in the U.S. and proximity of a property from a fracking well to disentangle the disclosure effects from concurrent and unrelated macroeconomic changes.

Using fracking disclosures and mortgage lending data, I find that properties close to a fracking well observe an increase in mortgage lending relative to properties far from a fracking well. The effects are stronger for properties that rely on groundwater as a drinking water source, consistent with the idea that water contamination concerns could have affected the lender's decision to lend to groundwater dependent properties. In line with the literature on the importance of soft information in lending decisions, the effects are stronger for lenders that are not in close proximity of residential properties. Although fracking disclosures result in an increase in lending for both good (low contamination risk) and bad (high contamination risk) news properties, the increase in lending is greater for properties where fracking disclosures provide good news compared to those where fracking disclosures provide bad news. By studying the effect of fracking disclosures on the level and the precision of property prices, I show that housing collateral channel appears to be the mechanism driving these results. Overall, these results suggest that non-SEC corporate disclosures by one sector of the economy can have a material spillover effect on economic activity in a different sector of the economy. Given the current debate on fracking chemical disclosures, these results also have important policy implications.

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Appendix: Variable Definitions

Variable Name	Definition (Source)
log(Sale)	Natural logarithm of sale price (in $ hundred thousand) (Corelogic)
log(Loan)	Natural logarithm of mortgage amount (in $ hundred thousand) (Corelogic)
Var(Sale)	Variance of sale prices (Corelogic)
Loan	Dummy variable: one if the sale was financed using a mortgage, zero otherwise (Corelogic)
LTV	Dollar value of mortgage scaled by dollar value of real estate transaction (Corelogic)
NLoan	Number of mortgage loans in a month in a state divided by the number of real estate transactions in the state in the same month
DLoan	Dollar value of mortgage loans in a month in a state divided by the dollar value of real estate transactions in the state in the same month
Post	Dummy variable: one beginning in the period in which disclosure regulation becomes effective for state, zero otherwise
Close	Dummy variable: one if the property was within 5 kilometers of at least one fracking well, zero if the property was beyond 5 kilometers but within 20 kilometers of at least one fracking well (FracFocus)
GW	Dummy variable: one if the property used groundwater as a source of drinking water, zero otherwise (State websites)
Toxic	Dummy variable: one if the property is close to at least one fracking well with at least one of the toxic chemicals, zero otherwise (SciFinder CAS, EPA reports)
Local	Dummy variable: one if the distance between the mortgage lender and the property is less than 25 miles, zero otherwise (Corelogic)

Figure 1: Sample Fracking Disclosure

The figure shows a sample fracking disclosure for a specific well in Kern county in California. Among other details, the well level disclosure provides information on the precise location of the fracking well as well as the name and concentrations of chemicals used in the extraction of oil and gas.

Hydraulic Fracturing Fluid Product Component Information Disclosure

Job Start Date:	2/10/2018
Job End Date:	2/10/2018
State:	California
County:	Kern - 30
API Number:	04-030-62130-00-00
Operator Name:	Chevron USA Inc.
Well Name and Number:	8-7DR
Latitude:	35.62268100
Longitude:	-119.72125500
Datum:	NAD83
Federal Well:	NO
Indian Well:	NO
True Vertical Depth:	1,824
Total Base Water Volume (gal):	115,453
Total Base Non Water Volume:	0

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
Fresh Water	Operator	Base Fluid					
			Water	7732-18-5	100.00000	76.67172	Density = 8.330. Additive Concentration in HF Fluid (% by mass) is 76.67172%
Ingredients	Listed Above	Listed Above					
			Water	7732-18-5	100.00000	0.21382	
DCA-13002	Halliburton	Breaker					
				Listed Below			
BC-140C	Halliburton	Crosslinker					
				Listed Below			
BE-3S BACTERICIDE	Halliburton	Biocide					
				Listed Below			
DCA-30001	Halliburton	Scale Inhibitor					
				Listed Below			
DCA-14005	Halliburton	pH Control Additive					
				Listed Below			
DCA-25005	Halliburton	Gelling Agent					
				Listed Below			
SAND-PREMIUM WHITE-16/30, BULK	Halliburton	Proppant					
				Listed Below			
GBW-30 BREAKER	Halliburton	Breaker					
				Listed Below			

Figure 2: Identification Strategy - Within States

The figure shows the classification of areas used for within state identification strategy. The center of the circle denotes a fracking well. I define properties within radius r_2 as treatment or close (area A) and properties beyond r_2 but within radius r_1 (area B) as control or far. Properties beyond radius r_1 (area C) are not a part of the sample.

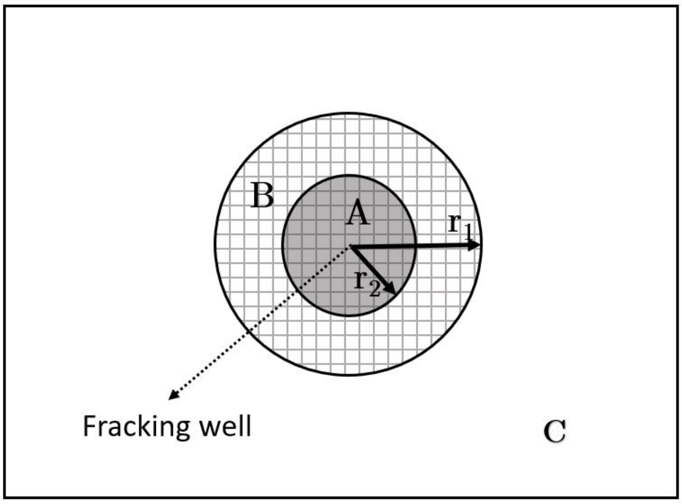
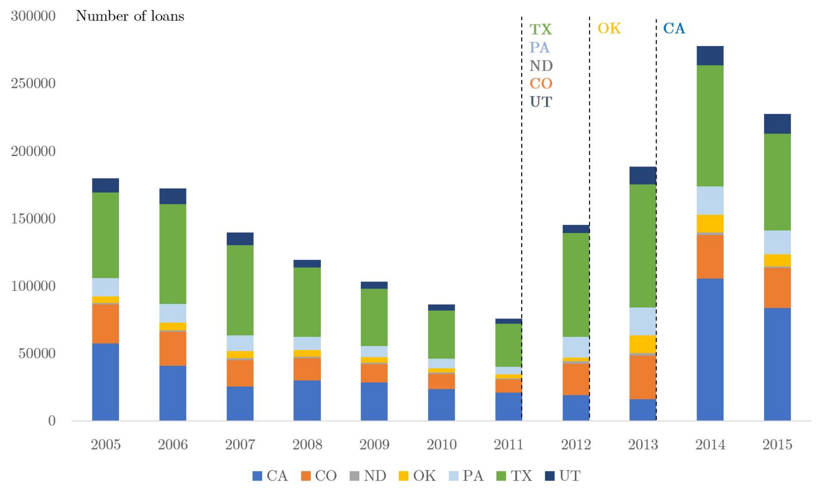


Figure 3: Mortgage Lending Before and After Disclosures

The figure shows a time trend of the number of mortgage loans in (a) and the dollar value of loans in (b) for my sample states. The vertical lines and state abbreviations denote the year in which disclosure regulation was implemented in respective states.

(a) Number of loans



(b) Dollar value of loans (in $Bn)

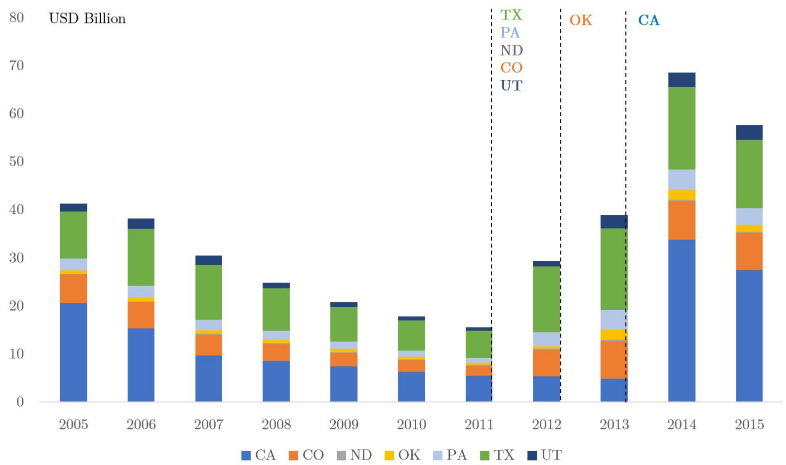


Figure 4: Sample Public Water Service Areas (California)

The following figure shows Public Water Service Areas (PWSA) in (a) and real estate properties mapped over PWSA in (b) for one of my sample states, California. The shaded blue area in (a) denotes the PWSA and unshaded areas are assumed to depend on private groundwater wells for drinking water. This figure demonstrates that PWSAs are scattered throughout the states and that there are large areas without access to piped water. The red points on the map in (b) denote the real estate properties in California that are part of my sample.

(a) PWSA

(b) Properties and PWSA

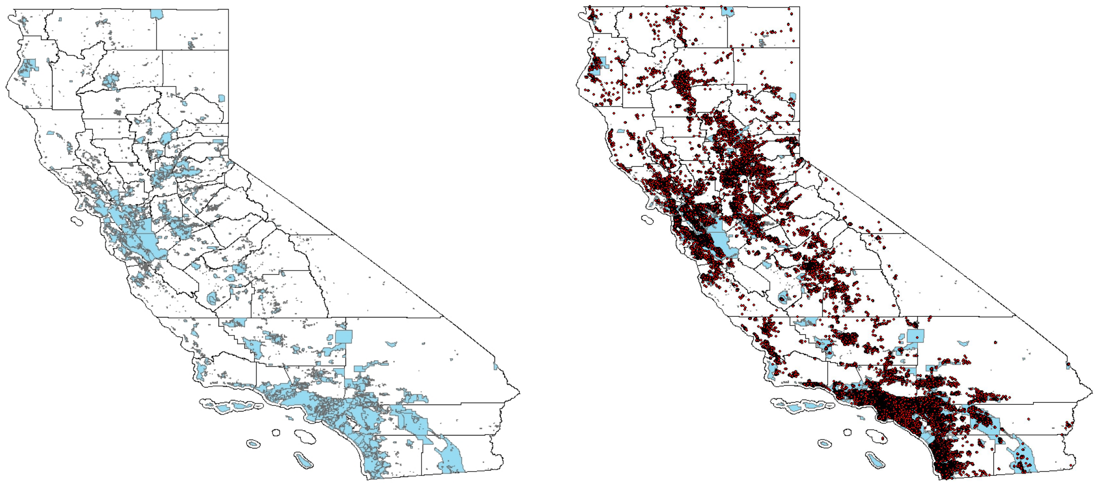


Table 1: Disclosure Regulations Across States

The table presents disclosure regulation laws across states with date of introduction and disclosure platform. This list excludes some states with little or no fracking activity. Konschnik and Dayalu (2016) provide a detailed survey of these state regulations. The states in bold are a part of my sample.

	Effective Date	Reporting Location
Alabama	09-Sep-2013	FracFocus
Arkansas	15-Jan-2011	State regulator
Colorado (CO)	01-Apr-2012	FracFocus
Kansas	02-Dec-2013	FracFocus or state regulator
Louisiana	20-Oct-2011	FracFocus or state regulator
Michigan	22-Jun-2011	State regulator
Mississippi	04-Mar-2013	FracFocus or state regulator
Montana	27-Aug-2011	FracFocus or state regulator
New Mexico	15-Feb-2012	State regulator
North Dakota (ND)	01-Apr-2012	FracFocus
Ohio	11-Jun-2012	FracFocus or state regulator
California (CA)[1]	01-Jan-2014	FracFocus or state regulator
Oklahoma (OK)[2]	01-Jan-2013	FracFocus or state regulator
Pennsylvania (PA)[3]	16-Apr-2012	FracFocus
Texas (TX)	01-Feb-2012	FracFocus
Utah (UT)	01-Nov-2012	FracFocus
West Virginia	29-Aug-2011	State regulator
Wyoming	05-Sep-2010	State regulator

[1] In California, reporting to the state (rather than on FracFocus) became mandatory on January 1, 2016 which is outside of my sample period.
[2] Oklahoma's regulations note that the state regulator will report to FracFocus any information it receives.
[3] Pennsylvania required reporting to the state in February 2011 but changed the reporting location to FracFocus in April 2012.

Table 2: Summary Statistics - Property Level Regressions

This table reports descriptive statistics for variables in full sample (a), the Far sub-sample (b) and Close sub-sample (c). Refer to the Appendix for variable definitions.

(a) Full Sample

	Pre-Disclosure				Post-Disclosure			
Variable	N	Mean	Median	SD	N	Mean	Median	SD
Loan	500,157	0.83	1.00	0.37	416,732	0.87	1.00	0.33
LTV	500,157	0.67	0.80	0.32	416,732	0.74	0.80	0.30
log(Sale)	500,157	12.11	12.12	0.73	416,732	12.20	12.22	0.68
log(Loan)	500,157	11.96	11.95	0.64	416,732	12.07	12.08	0.61
GW	415,558	0.23	0.00	0.42	341,810	0.23	0.00	0.42
Toxic	500,157	0.55	1.00	0.50	416,732	0.55	1.00	0.50

(b) Far Sub-sample

	Pre-Disclosure				Post-Disclosure			
Variable	N	Mean	Median	SD	N	Mean	Median	SD
Loan	345,496	0.83	1.00	0.37	286,191	0.86	1.00	0.34
LTV	345,496	0.67	0.80	0.32	286,191	0.73	0.80	0.31
log(Sale)	345,496	12.14	12.15	0.74	286,191	12.23	12.25	0.69
log(Loan)	345,496	11.99	11.98	0.65	286,191	12.09	12.10	0.62
GW	284,479	0.24	0.00	0.42	233,216	0.24	0.00	0.42
Toxic	345,496	0.54	1.00	0.49	286,191	0.54	1.00	0.49

(c) Close Sub-sample

	Pre-Disclosure				Post-Disclosure			
Variable	N	Mean	Median	SD	N	Mean	Median	SD
Loan	154,661	0.84	1.00	0.37	130,541	0.89	1.00	0.31
LTV	154,661	0.68	0.80	0.32	130,541	0.76	0.80	0.29
log(Sale)	154,661	12.04	12.06	0.70	130,541	12.15	12.16	0.64
log(Loan)	154,661	11.89	11.89	0.61	130,541	12.01	12.04	0.59
GW	131,079	0.20	0.00	0.40	108,594	0.20	0.00	0.40
Toxic	154,661	0.56	1.00	0.50	130,541	0.56	1.00	0.50

Table 3: Property-level Mortgage Lending Activity

The table presents results from the following regression specification

$$y_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}$$

The dependent variable is an indicator variable equal to one if the sale of property i at time t was financed by a mortgage, zero otherwise ($Loan_{i,t}$) in column (1) and mortgage loan scaled by the sale value of property i at time t ($LTV_{i,t}$) in column (2) for the sample period (2005-2015). Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varies with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) Loan	(2) LTV
Post	0.045***	0.040***
	(3.22)	(3.25)
Close × Post	0.026***	0.022***
	(14.92)	(14.28)
Observations	916,889	916,889
R-squared	0.6288	0.6132
Property FE	YES	YES
State × Year FE	YES	YES
Quarter FE	YES	YES

Table 4: Robustness - Mortgage Lending Activity [-2,+2]

The table presents results from the following regression specification

$$y_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}$$

The dependent variable is an indicator variable equal to one if the sale of property i at time t was financed by a mortgage, zero otherwise ($Loan_{i,t}$) in column (1) and mortgage loan scaled by the sale value of property i at time t ($LTV_{i,t}$) in column (2) for the sample period window of [-2,+2] years where 0 denotes the year-month of disclosure regulation. Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varies with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) Loan	(2) LTV
Post	0.152***	0.147***
	(4.15)	(4.44)
Close × Post	0.018***	0.018***
	(3.48)	(4.09)
Observations	116,290	116,290
R-squared	0.6763	0.6744
Property FE	YES	YES
State × Year FE	YES	YES
Quarter FE	YES	YES

Table 5: Aggregate Mortgage Lending Activity

The table presents results from the following regression specification

$$y_{i,t} = \alpha + \beta_1 Close_i + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} + \delta_{i,t} + q_t + \epsilon_{i,t}$$

The dependent variable is the total number of mortgage originations in state i year-month t scaled by the total number of real estate sales in the same period ($NLoan_{i,t}$) in column (1) and dollar volume of mortgage originations in year-month t scaled by the total dollar volume of real estate sales in the corresponding period ($DLoan_{i,t}$) in column (2) for the sample period (2005-2015). Refer to the Appendix for variable definitions. All specifications include a fixed effect that varies with both geography (state) and year ($\delta_{i,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on clustered standard errors at year-month level) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) NLoan	(2) DLoan
Close	-0.051***	-0.036***
	(-16.30)	(-10.49)
Post	0.050**	0.033*
	(2.28)	(1.79)
Close × Post	0.050***	0.036***
	(9.31)	(5.99)
Observations	1,594	1,594
R-squared	0.9197	0.8448
State × Year FE	YES	YES
Quarter FE	YES	YES

Table 6: Cross-Sectional Analysis - Drinking Water Source

The table presents results from the following regression specification

$$
\begin{aligned}
y_{i,t} = {} & \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} \\
& + \beta_3 Close_i \times GW_i \times Post_{i,t} \\
& + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}
\end{aligned}
$$

The dependent variable is an indicator variable equal to one if the sale of property i at time t was financed by a mortgage, zero otherwise ($Loan_{i,t}$) in column (1) and mortgage loan scaled by the sale value of property i at time t ($LTV_{i,t}$) in column (2) for the sample period (2005-2015). Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varied with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) Loan	(2) LTV
Post	0.011	0.010
	(1.38)	(1.37)
Close × Post	0.024***	0.019***
	(14.14)	(12.64)
Close × GW × Post	0.006**	0.011***
	(2.58)	(4.81)
Observations	757,368	757,368
R-squared	0.6755	0.6550
Property FE	YES	YES
State × Year FE	YES	YES
Quarter FE	YES	YES
F Stat: Close × Post + Close × GW × Post = 0	164.6	186.5
p-value: Close × Post + Close × GW × Post = 0	0.00	0.00

Table 7: Cross-Sectional Analysis - Lender Type

Column (1) and (2) present results from the following regression specification for local and global sub samples, respectively:

$$LTV_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}$$

Column (3) presents results from the following regression specification:

$$LTV_{i,t} = \alpha + \beta_1 Close_i \times Local_{i,t} + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} + \beta_4 Close_i \times Local_{i,t} \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}$$

The dependent variable is mortgage amount scaled by the sale value of property i at time t for the sample period (2005-2015). Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varied with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

	(1)	(2)	(3)
	Local Subsample	Global Subsample	Total Sample
VARIABLES	LTV	LTV	LTV
Close × Local			-0.006***
			(-3.33)
Post	0.002	-0.005	-0.001
	(0.46)	(-1.28)	(-0.48)
Close × Post	-0.001	0.002**	0.007***
	(-0.29)	(2.00)	(8.03)
Close × Post × Local			-0.017***
			(-7.79)
Observations	205,554	459,820	665,374
R-squared	0.8720	0.7672	0.6848
Property FE	YES	YES	YES
State x Year FE	YES	YES	YES
Quarter FE	YES	YES	YES

Table 8: Cross-Sectional Analysis - Good News vs. Bad News

The table presents results from the following regression specification

$$y_{i,t} = \alpha + \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} + \beta_3 Close_i \times GW_i \times Post_{i,t} + \beta_4 Close_i \times GW_i \times Toxic_i \times Post_{i,t} + \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t}$$

The dependent variable is an indicator variable equal to one if the sale of property i at time t was financed by a mortgage, zero otherwise ($Loan_{i,t}$) in column (1) and mortgage loan scaled by the sale value of property i at time t ($LTV_{i,t}$) in column (2) for the sample period (2005-2015). Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varied with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) Loan	(2) LTV
Post	0.011	0.010
	(1.38)	(1.37)
Close × Post	0.024***	0.019***
	(14.14)	(12.63)
Close × GW × Post	0.013***	0.011***
	(4.07)	(3.71)
Close × GW × Toxic × Post	-0.013***	-0.000
	(-3.63)	(-0.14)
Observations	757,368	757,368
R-squared	0.6755	0.6550
Property FE	YES	YES
State × Year FE	YES	YES
Quarter FE	YES	YES

Column (1):
F Stat: Close × Post + Close × GW × Post = 0: 125.8 (0.00)
F Stat: Close × Post + Close × GW × Post + Close × GW × Toxic × Post = 0: 92.98 (0.00)
Column (2):
F Stat: Close × Post + Close × GW × Post = 0: 97.09 (0.00)
F Stat: Close × Post + Close × GW × Post + Close × GW × Toxic × Post: 136.5 (0.00)

Table 9: Mechanism - Effect of Disclosures on the Precision of Sale Prices

The table presents results from the following regression specification in column (1):

$$Var(Sale)_{i,t} = \alpha + \beta_1 Close_i + \beta_2 Post_{i,t} + \beta_3 Close_i \times Post_{i,t} + q_t + \epsilon_{i,t}$$

The dependent variable is the variance of sale prices for properties sold in state i at time t in close or far areas. Column (2) reports results for the following regression specification:

$$\begin{aligned} Var(Sale)_{i,t} = \alpha &+ \beta_1 Close_i + \beta_2 Close_i \times GW_i + \beta_3 Close_i \times GW_i \times Toxic_i \\ &+ \beta_4 Post_{i,t} + \beta_4 Close_i \times Post_{i,t} + \beta_5 Close_i \times GW_i \times Post_{i,t} \\ &+ \beta_3 Close_i \times GW_i \times Toxic_i \times Post_{i,t} + q_t + \epsilon_{i,t} \end{aligned}$$

The dependent variable is the variance of sale prices for properties sold in state i at time t in close/far, groundwater/piped-water dependent and toxic/non-toxic areas. Refer to the Appendix for variable definitions. The specification includes a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) Var(Sale)	(2) Var(Sale)
Close	0.039***	0.023***
	(5.52)	(3.28)
Close × GW		0.075***
		(5.95)
Close × GW × Toxic		-0.050***
		(-2.97)
Post	-0.042***	-0.013
	(-5.14)	(-1.31)
Close × Post	-0.029***	-0.048***
	(-2.80)	(-4.11)
Close × GW × Post		0.019
		(0.89)
Close × GW × Toxic × Post		-0.012
		(-0.40)
Observations	1,554	4,366
R-squared	0.0359	0.0231
Quarter FE	YES	YES

Table 10: Mechanism - Effect of Disclosures on Sale Prices

The table presents results from the following regression specification

$$\begin{aligned} log(Sale)_{i,t} = \alpha &+ \beta_1 Post_{i,t} + \beta_2 Close_i \times Post_{i,t} \\ &+ \beta_3 Close_i \times GW_i \times Post_{i,t} \\ &+ \beta_4 Close_i \times GW_i \times Toxic_i \times Post_{i,t} \\ &+ \delta_{s,t} + \gamma_i + q_t + \epsilon_{i,t} \end{aligned}$$

The dependent variable is natural logarithm of sale price of property i at time t. Refer to the Appendix for variable definitions. All specifications include a property fixed effect (γ_i), a fixed effect that varied with both geography (state) and year ($\delta_{s,t}$), and a temporal fixed effect indicating the quarter (q_t). T-statistic (based on standard errors clustered by property and year-month) is reported in parentheses; *, **, and *** denote significance at the 10%, 5% , and 1% respectively.

VARIABLES	(1) log(Sale)
Post	0.052***
	(5.01)
Close × Post	-0.003
	(-1.06)
Close × GW × Post	0.027***
	(4.23)
Close × GW × Toxic × Post	-0.022***
	(-2.84)
Observations	757,368
R-squared	0.8755
Property FE	YES
State x Year FE	YES
Quarter FE	YES