Do Firms Experiencing More Wildfires Disclose More Wildfire Information in Their 10-Ks?

By: Paul Griffin, Yijing Jiang and Estelle Sun

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Abstract. Wildfires pose a significant risk that threatens firm value. That risk may have risen significantly in recent years in light of record-breaking wildfires in the United States and elsewhere. It is an open question, however, whether such increasing wildfire risk affects firms' disclosures of wildfire-related information. We match the location of wildfires in the United States to firms with headquarters in the same county as the wildfire. Based on a difference-in-difference design and other econometric tests and methods, we find that firms exposed to more wildfire days on average provide more textual 10-K disclosure of wildfire-related information in their filings compared to firms exposed to fewer wildfire days. Our results are also significant economically. For example, when firms experience three versus zero wildfire days this increases 10-K wildfire word count by 50 percent. We attribute this positive relation to increasing trends in climate change risks and disclosure requirements related to heightened wildfire concerns. These concerns emanate mainly from wildfire-exposed firms in the western states, in the utility and banking industries, those exhibiting a high level of tangible assets, and those having experienced wildfire impacting their past operations. Overall, the findings deepen our knowledge of a heretofore unstudied risk factor important for firm value.

Keywords. Wildfire risk, wildfire geography, 10-K textual disclosure, disclosure regulation.

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1 Introduction

Recent catastrophic wildfires in Australia and California have sparked important questions on environmental risk (Lindenmayer and Taylor 2020; Williams et al. 2019). Wildfires have been estimated to produce pyrogenic CO₂ that can exceed 50 percent of fossil fuel emissions (Jolly et al. 2015). While people and governments shoulder much of that risk, a mounting interest has emerged on the issue of whether financial markets adequately consider wildfire risk in assessing firm value. Wildfire risk is unique in several ways. It combines multiple climate-related factors such as fuel aridity from vapor pressure, water deficits, wind speed, and extreme heat. Some of these factors, moreover, are anthropogenic (Abatzoglou and Williams 2016; Goss et al. 2020; Mann et al. 2016). Wildfire risk also results from the design of flammable ecosystems. These require policies of land management for multiple uses such as agriculture and human settlement. This combination of natural and human-caused meteorological factors combined with regulatory policies has created a surge of devastating and costly wildfire activity, now at record levels in many parts of the world. These record levels have drawn the attention of policymakers and the media and, increasingly, how firms and investors should respond to the surge.

Despite advanced tools for assessing wildfire risk, public agencies and private-sector companies continue to grapple with this issue of wildfire risk assessment. Some insurance companies have concluded that they cannot price this risk because the future costs of wildfires are largely unknowable. In this paper, we address the open question of whether firm managers might recognize this risk. Specifically, we ask whether firm managers' disclosures of wildfire-related information in their regulatory filings vary in response to firms' direct exposure to wildfires. We then address which firms might be most exposed to wildfire risk and whether these firms have changed their extent of wildfire disclosure in light of growing threats to firm value. These threats

emanate from costlier and more uncertain levels of property destruction and assessments of additional liability from wildfires.

As our identification strategy, we exploit spatial and temporal variation in the number of days in a year of firms' direct exposure to wildfires in the same location as the headquarters of a firm.¹ We then layer these wildfire days data on firms' 10-K textual disclosures of wildfire-related information. This allows us to examine whether firms' 10-K textual disclosures of wildfire-related information vary predictably based on the level of firms' direct wildfire exposure. We address this question using a variety of econometric specifications. We supplement our main analysis using a difference-in-difference design to control for unobservable time-invariant differences between firms exposed to wildfire and otherwise equivalent firms not exposed to wildfire.

Wildfires are not new. What *is* new is the recent recognition of wildfire disclosure by listed public companies, although this is far from widespread. For example, our data (Table 1) indicate that whereas 3.5 percent of wildfire-exposed firms disclose the event in the 10-K in 1996 still only 51.4 percent of wildfire-exposed disclose in 2018 (the last year of our dataset). In part because of this pattern of under-disclosure despite the evidence of record levels of physical risk, it is unclear ex-ante whether we would observe that firms with more wildfire exposure disclose significantly more wildfire-related information than firms with less wildfire exposure. On the one hand, we predict an increase in disclosure. The probability of firms having direct impacts from wildfire on their physical plants and facilities, and also on their manufacturing and distribution processes, is much higher when firms are exposed to more wildfire days versus fewer wildfire days. The former firms, thus, are more likely to consider wildfire a material risk factor and disclose this risk in their

¹ We use historical data to establish a firm's headquarters, as headquarter locations can change over time. We also consider alternatives to headquarter location, including identifying the location of firms' operations based on mentions of state names in selected item numbers in a firm's 10-K (García and Norli 2012). Section 5 details the results.

10-Ks. Regulation S-K has long required companies to disclose their significant risk factors in the 10-K filings. More recently, SEC Interpretive Release (SEC 2010) issued guidance for firms to provide climate change disclosure in their 10-Ks consistent with the legal standard of materiality.² By enhancing their understanding of firms' wildfire assessments and risk management practices, wildfire-related disclosure can reduce firm uncertainty and users' risk perceptions, and consequently contribute to higher firm value.

On the other hand, despite a growing awareness of the strategic importance of climate change, disclosures of climate risks remain the exception rather than the norm. Doran and Quinn (2009) find that more than three-quarters of the S&P 500 firms fail to provide any mention of climate change in their 10-K filings between 1995 and 2008. Baier et al. (2020) show that the average word count of environmental disclosure to total words in 10-Ks is only 0.10 percent. Given the scarcity of climate risk disclosure, we may not observe wildfire-exposed firms providing more wildfire-related disclosure. Several reasons may explain this. First, wildfire risk reflects one aspect of firms' environmental concerns. Some firms, thus, may prefer to withhold negative news due to its adverse implication for firm value (Ahn et al. 2019; Bao et al. 2019; Hutton et al. 2009; Kothari et al. 2009; Nagar et al. 2003). This is possible especially when the extent of monitoring and enforcement is limited. The materiality threshold is a second reason for a lack of wildfire disclosure. Firms in certain industries such as services may not consider wildfire a material risk factor. Third, firms' preference for boilerplate instead of specific language for negative events could lead to limited disclosure. Using vague and boilerplate language is a common issue for the risk factors in 10-K filings. Firms may refer to general climate risk only to avoid mentioning specific events such

² While some firms may also disclose wildfire information in other regulatory reports, such as an 8-K or 10-Q filing, those reports tend to be replicative of 10-K information, especially if deemed sufficiently material for disclosure under Regulation S-K. For the same reason and also because of its voluntary and sometimes self-serving (Delmas and Burbano 2011), we exclude an analysis of wildfire disclosure in sustainability reports.

as wildfires. Fourth, companies may be able to purchase insurance (such as property liability insurance) to cover part of the wildfire risk and, thus, have less need to disclose.

While wildfire-exposed firms could, on average, disclose more or less wildfire-related information, we also predict that they should have increased disclosure more in the recent years and for certain types of firms with heightened wildfire concerns. Specifically, we hypothesize that firms' disclosure should increase over time, and mostly around and after 2010 due to the guidance of the SEC on climate risk disclosure (SEC 2010). We also predict larger wildfire-exposed firms to disclose more since they have more resources to assess their wildfire risk and may receive more monitoring and scrutiny from investors and stakeholders. In addition, larger firms cannot be exempted from the SEC's guidance, but small firms can. Wildfire-exposed firms could also disclose more when they are located in the western United States, in the utility and banking industries, and exhibit a high level of tangible assets. These firms are naturally and contractually more exposed to wildfire risk. As such, they may respond more sharply to wildfire events. Lastly, we explore the probability that wildfire-exposed disclosure relates to firms that have experienced wildfire events impacting their past operations. Specifically, we argue that wildfire mentions in the forward-looking statements, item 1 (business), or item 1A (risk factors) of the 10-K filings are more likely to refer to a general description of firms' wildfire risk. By contrast, wildfire mentions in other 10-K items, such as legal proceedings, financial statements, and exhibits, are likely to reflect wildfire events that have affected their past operations. Relying on this distinction, we predict that firms with wildfire activities affecting their past operations should disclose more than those emphasizing future risks.

Our empirical tests yield several important insights. We first find that firms located in a county with more wildfire days per year on average provide more textual disclosure of wildfire-related

information in their 10-K filings in the year of the wildfires compared to firms with fewer wildfire days. Second, this positive relation is largely driven by the later years of our study. This is consistent with increasing wildfire concerns in recent years and the release of the SEC guidance on climate change disclosure (SEC 2010). This positive relation is also mostly explained by larger firms, consistent with them facing more public scrutiny and a lower likelihood of exemption from the SEC disclosure release. Third, consistent with higher wildfire risk prompting more disclosure, we find higher levels of wildfire disclosure for wildfire-exposed firms located in the western states, in the utility and banking industries, and with larger than median tangible assets. Fourth, our analysis of the disclosure location of the wildfire-related information indicates that 68.8 percent of the firm-year observations mention wildfire in the 10-K sections on forward-looking statements (2.5 percent), business description (Item 1, 13.3 percent), and risk factors (Item 1A, 53.0 percent). MD&A and market risk disclosures (Item 7 and Item 7A) contribute an additional 15.9 percent. The remaining disclosures are spread over several other 10-K locations (Item 2—properties, Item 3—legal proceedings, Item 6—selected financial data, Item 8—financial statements, Item 14—accounting fees and services, Item 15—exhibits and tables, the audit report, and the management internal control report). We use the disclosure location to imply the differing wildfire risk impact faced by a firm. We argue that firms that discuss wildfire-related information in Items 2, 3, 6, 7, 7A, 8, 14, 15, the audit report, or the management internal control report are more likely to have experienced wildfire events affecting their past operations and, thus, should disclose more. Our results confirm this expectation. Lastly, our results hold under different specifications of the regression model. These include a difference-in-difference analysis of treatment (experience wildfire) and control (do not experience wildfire) firms before and after the shock of a wildfire

occurrence and an analysis that measures wildfire exposure incorporating firms' operations across multiple states rather than relying on headquarter county alone.

Our study contributes to the accounting literature in several ways. First, it adds to the literature's long-standing interest in environmental reporting. Despite its attention to both voluntary and mandatory environmental disclosures, evidence of firms' 10-K disclosure on climate change, particularly regarding wildfire-related information, is still very limited. Nevertheless, our evidence indicates that wildfire disclosure increases significantly around and after 2010, consistent with the SEC Guidance (SEC 2010). That guidance specifically requires firms to consider severe (i.e., extreme) weather as a material risk factor in 10-K filings.

Second, our study contributes to the literature seeking to identify the determinants of environmental disclosure. We show that firms' proximity to wildfire events and the duration of wildfire exposure are significant determinants of wildfire disclosure in 10-Ks. Firms in the western states, in the utility and banking industries, those exhibiting a high level of tangible assets, and those having experienced wildfire events affecting their past operations also contribute as key factors to explain the level and trend of wildfire disclosure.

Third, prior work examining the relation between climate risks and disclosure focuses largely on risks associated with greenhouse gas and carbon emissions. These studies are subject to the classic causality issue, that is, emission risks lead to more disclosure, which simultaneously affects the level of emission risks. While we cannot pinpoint a precise mechanism by which the duration of a wildfire event triggers actions by firm managers due to the lack of high-frequency data on firms' disclosure responses, we can reasonably rule out reverse causation because wildfire events are exogenous to managers' actions.

Finally, we contribute to the broader literature on textual disclosure in financial statements. This literature, so far, has focused mainly on investors' recognition of financial risk factors in firms' 10-K filings (e.g., product market competition). By being the first to explore wildfire-related information in 10-K filings, we deepen our knowledge of a heretofore unstudied risk factor important for firm value.³ We structure our paper as follows. Section 2 discusses the related literature and motivates the testable hypotheses. Section 3 summarizes the data and sample and states the models. Section 4 presents the results. Section 5 summarizes additional analyses. Section 6 concludes.

2 Related Literature and Hypotheses

2.1 Prior literature

Our study builds on the literature on textual analysis and environmental performance and disclosure. Studies on textual analysis in financial reports initially examined the extent of adoption of the Global Reporting Initiative framework (GRI) in CSR reports. Clarkson et al. (2008) develop a voluntary disclosure index based on the GRI guideline and find a positive relation between environmental performance and environmental disclosure. Clarkson et al. (2013), using the same methodology in Clarkson et al. (2008), further show that CSR disclosure is value relevant. Lokuwaduge and Heenetigala (2017) also relate CSR disclosure to categories in the GRI sustainability framework. They find that although the GRI framework is widely known, 63 percent of the GRI environmental indicators are not used to report environmental performance by the Australian mining companies.

³ While ours is not a paper on the market consequences of wildfire disclosure, the act of wildfire disclosure in a 10-K by a firm *is* tantamount to that firm believing that the disclosure provides material (i.e., price-sensitive) information for investors. We test and document results on this idea in a later section.

A younger literature examines relations between managers' incentives and textual CSR disclosures in SEC filings. One group of studies documents a limited extent of CSR disclosure under SEC guidance. For example, Doran and Quinn (2009) report that the vast majority of S&P 500 firms remain silent concerning the risks and opportunities posed by climate change. For those that do disclose, the quality of the discussion (i.e., the percent of firms that identify at least one climate risk and articulated a strategy for managing the risk) is low. Baier et al. (2020) find that the average percentage of words of governance, social, and environmental disclosure to total words in 10-Ks is 1.66 percent, 0.28 percent, and 0.10 percent, respectively.

Other studies provide evidence suggesting managers' opportunistic use of CSR disclosure in 10-K filings. Loughran et al. (2009) document that firms using ethics-related terms in their 10-K filings are more likely to be "sin" stocks, the object of class action lawsuits, and score poorly on measures of corporate governance. Cho et al. (2010) find that managers of firms with worse environmental performance bias their language in 10-K filings to give a favorable but less certain impression than their better-performing counterparts. Two recent studies examine CSR disclosure in 10-Ks and market valuation and competitiveness. Berkman et al. (2019) show that their measure of firm-specific climate risk exposure associates negatively with firm value and positively with the implied cost of capital. Cannon et al. (2020) show that 10-K CSR disclosure relates to competitive advantage across firms.

By focusing on broad categories of CSR or environmental risk, these studies document results that are only indirectly germane to textual disclosure on wildfires. For instance, we could not find specific analyses of quantitative or qualitative wildfire-related information in financial reports. This is interesting because wildfire risk is not a novel phenomenon. Our dataset indicates that 10-K disclosure on wildfire-related risk dates back to at least 1996, the first year of our study period.

Significant wildfire events in the US date back much further, although their costs were likely lower. For example, according to the data from the National Interagency Fire Center, fire suppression costs in 2017 exceeded the inflation-adjusted cost of suppression efforts in 1985 by more than five times.

Recent catastrophic and costly wildfires have spotlighted the need for research on wildfire risk as a financial valuation factor. While a healthy literature examines the cost of wildfires from a macroeconomic perspective (for a review, see Thomas et al. 2017), the number of studies so far on the firm-value impacts of wildfires is small (Asbi et al. 2020; Cleetus and Mulik 2014; Williams et al. 2019). Much of this firm-level literature, moreover, relates to wildfire risk for insurance pricing purposes (CoreLogic 2019). Some reports document serious weaknesses in wildfire risk assessment, risk management, and preparedness to explain risk mispricing. Partly in response, insurance companies have increased their rates. Other reports indicate that some insurance companies have withdrawn from high risk or unknowable wildfire risk sectors because the current system is untenable (State_of_California 2019). Higher costs of insurance and the potential lack thereof pose a threat to firm value, especially for firms in fire-prone locations. Raising prices does not, however, generate better wildfire risk assessments. To generate more accuracy, insurance companies have increased their use of geospatial imagery and artificial intelligence (e.g., Zesty.ai 2020). By linking wildfire risk to firms' operations at a granular level, this allows for more accurate risk pricing.⁴ These insurance trends suggest that firms today should be more aware than before of the cost of wildfire protection for their properties.

⁴ Jolly et al. (2015) document that the burnable areas affected by global fires doubled between 1979 and 2013, mainly because of longer fire seasons. These results for the United States were mostly explained by warmer weather, lower humidity, longer rain-free intervals, and higher wind speeds.

2.2 Hypotheses development

Wildfires can adversely affect firms' financial statements in several ways. First, firms exposed to more wildfire days are more likely to have property damage and business interruption, leading to significant losses. If wildfire events affect firms' local supply chains, they could also have a material effect on their operations. Second, such events are also relevant from a financial reporting perspective since the SEC requires material risk disclosure in 10-Ks. Third, the negative implications for firm value will likely increase investors' demand for wildfire-related information to better assess their risk portfolios. Fourth, in addition to capital market pressure, these firms are also exposed to pressure from other stakeholders (Cho and Patten 2007) and through social media. Social media data allow interested parties to trace the follow-on effects of wildfires. These include an increase in deaths, air pollution, psychological impacts, and other adverse health outcomes (Boulton et al. 2016; Jiang et al. 2019). These significantly increase the public scrutiny on firms. They may also incentivize managers to disclose their wildfire risk exposure and risk mitigation practices to reduce firm uncertainty and users' risk perceptions. In short, viewed as material events with physical, economic, and social impacts, we expect to observe an increase in wildfire-related disclosure for firms located in counties with more wildfire days, relative to firms located in counties with fewer wildfire days.

Alternatively, with improved wildfire risk assessment and better pricing of insurance contracts, firms' exposure to the uncovered risks of wildfires might not necessarily increase. As such, we might not observe an increase in wildfire-related disclosure.⁵ Firms' disclosure on wildfires could also be limited for three additional reasons. First, firms in less fire-prone locations may find the

⁵ As a check on whether firms might mitigate wildfire risk through insurance, we follow prior research (Angbazo and Narayanan 1996; Lamb 1998) and test for a negative stock price reaction of insurance companies that might cover firms' losses around the dates of potential wildfire claims by firms not in the insurance industry (Section 5.3).

wildfire effect on themselves immaterial and, thus, do not need to disclose. Second, given that wildfire risk has negative connotations for firm value, managers might strategically decide to under-report this risk in regulatory filings (Ahn et al. 2019; Bao et al. 2019; Hutton et al. 2009; Kothari et al. 2009; Nagar et al. 2003). Third, boilerplate disclosure is common to the non-financial sections of 10-K filings. Prior research finds that firms tend to greenwash events that have adverse outcomes for firm value (Lyon and Maxwell 2011). Therefore, firms may use a more general description of the different kinds of climate change risk instead of referring to specific risks such as wildfire risk. Hence, in this alternative scenario, we might not observe an increase in wildfire-related information in 10-K filings, other than in vague terms.

Building on these two-sided arguments, our first hypothesis in null form is:

H1: There is no relation between firms with greater exposure to wildfire events and their textual disclosure of wildfire-related information in 10-K filings.

Next, we investigate whether the extent of wildfire disclosure might have increased in recent years in light of the increasing toll of wildfires on people and businesses. Heightened public awareness and strategies for increased disclosure to mitigate the rising threat of litigation may have also caused such an increase. Further, in 2010, SEC released interpretative guidance that obliges firms to provide material climate change information in 10-K filings (SEC 2010). Citing the results of a 2007 US Government Accountability Office (GAO) report (GAO 2007) which states that “88% of all property losses paid by insurers between 1980 and 2005 were weather-related,” the release identifies potential risks to the company, its assets, supply chain, and other areas from the physical impact of severe weather. Although the SEC published its Release 33-9106 in 2010, consideration of proposals to clarify climate change reporting has been ongoing at least from 2007. Freedman et al. (2015) document a significant increase in 10-K climate change disclosure starting in 2009,

concluding that many firms anticipated the SEC's guidance rules and reacted early. Therefore, if the SEC release has any effect on the wildfire risk reporting, there should be an increase in wildfire disclosures around and after 2010. Our second hypothesis is:

H2a: Firms with greater exposure to wildfire events increase their textual disclosure of wildfire-related information in 10-K filings around and after 2010.

Prior environmental disclosure has documented a strong positive relation between firm size and disclosure (e.g., Cho and Patten 2007; Clarkson et al. 2008; Cormier and Magnan 1999). Larger firms have more recourse to assess their wildfire risk and disseminate related information. They are also under greater monitoring and scrutiny from investors and stakeholders, and thus more disclosure helps relieve the wildfire concerns from the public. Furthermore, larger firms cannot be exempted from SEC's guidance on climate risk disclosure, whereas small reporting firms can. We, therefore, predict that larger wildfire-exposed firms increase their wildfire disclosure more than similar firms with smaller sizes.

H2b: Firms with greater exposure to wildfire events increase their textual disclosure of wildfire-related information in 10-K filings when they are larger.

As the third set of hypotheses, and to enhance identification, we test for predictable differences in 10-K wildfire textual disclosure by firms with heightened wildfire concerns. First, we predict that wildfire-exposed firms in the western states (i.e., AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, WY) will disclose more given their fire-prone locations and the fire-weather conditions, e.g., high temperatures, high wind speed, and low precipitation. Second, certain industries are naturally and contractually more exposed to wildfire losses and future wildfire risk. Utility firms are the top on the list, as they have often been found to be the cause of the wildfires. They can be liable for substantial costs, including fire suppression, damages to structures, and damages to other economic and natural resources. Banks can also be significantly affected by wildfires. Other than their direct

exposure to wildfires, they also face increasing credit costs because of the physical and economic damages to their local borrowers. Third, we predict that wildfire-exposed firms with significant tangible assets (inventory and property, plant, and equipment) will have higher levels of 10-K wildfire disclosure. The physical damage to their inventories and facilities as a result of wildfires should be larger and costlier than firms with limited tangible assets. Taken together, we predict that wildfire-exposed firms in the west region, in the utility and banking industries, and exhibiting a high level of tangible assets have higher wildfire disclosure than their counterparts.

H3: Firms with greater exposure to wildfire events increase their textual disclosure of wildfire-related information in 10-K filings when they are in the west region, in the utility and banking industries, and exhibiting a high level of tangible assets.

Lastly, we examine whether wildfire-exposed firms that may have experienced wildfire events that affected their past operations disclose more. We measure the likelihood of wildfire exposure that may have affected firm operations using the disclosure location of wildfire-related information in 10-Ks. A 10-K report consists of several items each of which serves a unique purpose. When firms mention wildfires in the forward-looking statements, Item 1 (business description), or Item 1A (risk factors), they are likely providing a general description of firms' wildfire risk. The discussions are mostly forward-looking in nature. When firms mention wildfires in other items, such as Item 3 (legal proceeding) and Item 8 (financial statements and footnotes), they are likely indicating that certain wildfire events have affected firms' past operations. Relying on this distinction, we define a high likelihood of wildfire exposure that may have affected firms' past operations when firms disclose wildfire-related information in Items 2 (properties), 3 (legal proceedings), 6 (selected financial data), 7 (MD&A), 7A (market risk disclosure), 8 (financial statements), 14 (accounting fees), 15 (exhibits), the audit report, or the management internal

control report. We predict that wildfire-exposed firms that have likely experienced wildfire events affecting their past operations have higher wildfire disclosure than their counterparts.

H4: Firms with greater exposure to wildfire events increase their textual disclosure of wildfire-related information in 10-K filings when the wildfires are likely to have affected their past operations.

3 Data and Sample, Variables and Models

3.1 Data and sample

Our tests employ data from three sources. First, we obtain data on wildfires from the National Centers for Environmental Information Storm Events dataset (NOAA 2018a). This dataset identifies wildfires as “any significant forest fire, grassland fire, rangeland fire, or wildland-urban interface fire that consumes the natural fuels and spreads in response to its environment. ‘Significant’ is defined as a wildfire that causes one or more fatalities, one or more significant injuries, and/or property damage.” (NOAA 2018b). The dataset lists the coordinates of each fire, the counties in which the fire occurs, its duration in days (from the out-of-control date to the under-control date), the dollar damages, and the number of fatalities if any.

Second, we obtain financial information and the location (state and county zip code) of firms’ headquarters from Compustat. We use the zip code information to assign firm headquarters to counties. Next, we match the fire events to firms at the county level. If a fire covers more than one county, all firms headquartered in those counties would be affected by the same wildfire event. Thus, they have the same number of wildfire days associated with that wildfire event. This way, for each firm-year observation, we calculate the number of total wildfire days in the county of a company's headquarters during a fiscal year. For firms with no wildfires in their headquarters' county during the fiscal year, the number of total wildfire days is set to zero. Panel A of Appendix 1 summarizes the wildfire distribution by county. We observe that wildfire events are dominated

in the western regions as well as some southern regions. Panel B shows the distribution of wildfire days for counties with headquarters in our sample. Again, the West Coast, East Coast, and Florida are the main areas with headquarters in counties experiencing wildfires. Panel C lists the number of wildfire day counts in each county. States such as California, Oregon, Washington, Arizona, Colorado, and Wyoming have wildfires with the longest durations. Panel D compares the wildfire day counts for 1996–2008 and 2009–2018. Both the number of exposed counties and the number of wildfire days per county have increased.

Third, we extract textual information in the firm’s 10-K related to wildfires from SEC Edgar. We use the words “wildfire” or “wild fire” to identify wildfire-related information.⁶ After identifying each 10-K report with wildfire-related information, we then count the number of wildfire mentions in the filing.⁷ Appendix 2 illustrates the word count in 2016 for the utility PG&E Corporation (eight mentions in 10-K Items 1, 1A, 3, 7, and 8) and insurer Cincinnati Financial Corporation (two mentions in 10-K Item 1A).

Overall, we start with a sample of 219,659 firm-year observations in Compustat from 1996 to 2018. We begin from 1996 as this is the first year the wildfire data is available from NOAA. We end the dataset in 2018, as the most recent full-year SEC Edgar data from the William McDonald web site (<https://sraf.nd.edu/textual-analysis/resources/>) stops in 2018. We lose 71,860

⁶ We also consider the use of the word “fire” to search for wildfire-related filings but ended up with many filings unrelated to wildfires. Examples are products containing the word “fire”, such as fire alarm, firewall, fireplace, and description of electricity power, such as fuel-fired, coal-fired, etc. While the use of the specific word wildfire has the advantage of identifying precisely only filings with wildfire Information, it has the disadvantage of excluding 10-K filings that use “fire” or “fires” to identify wildfire-related information.

⁷ Our choice of a word-count measure for this initial study of wildfire disclosure is motivated by simplicity and ease of interpretation of the results. While more complex measures are available, it is unclear how a more complex measure would be more useful for examining our research question. For example, a sentiment or tonal measure would provide little additional variation because wildfire mentions represent mostly negative (additional risk) and not positive news (additional opportunities).

observations from missing 10-K filings in Edgar.⁸ Our sample further decreases by 54,485 and 7,129 observations due to the missing financial variables and stock return data in Compustat and CRSP, respectively. The final sample includes 86,185 firm-year observations. Of this sample, 8,654 experience wildfires in their headquarter counties; and 1,587 disclose wildfire-related information in their 10-K reports. While wildfires and 10-K disclosure are recorded in firm-years. In terms of sequencing, the wildfires always occur before the 10-K release date. This helps establish a causal relation between wildfire occurrence and 10-K disclosure.

3.2 Variables

Table 1 summarizes the variables used in our analysis. Variable definitions are listed in Appendix 3. Panel A presents descriptive statistics of the variables for the entire sample. We winsorize all continuous variables at the 1 percent and 99 percent percentiles. First, we observe that the mean value of the number of the wildfire word count (*WILDFIRE_WORDCNT*) and the occurrence of wildfire disclosure (*D_WILDFIRE_WORDCNT*) are low. For example, only 1.8 percent of the sample mentions wildfire in its 10-K filings in a year (*D_WILDFIRE_WORDCNT*). The number of wildfire days, however, is much higher. Our sample firms experience, on average, one wildfire day in their headquarter counties in a year (0.986, *WILDFIRE_DAYCNT*), and ten percent of the sample experienced at least one wildfire in its headquarter county in a year (*D_WILDFIRE_DAYCNT*). Second, the financial variables are mostly consistent with prior research. Our sample firms have an average of \$3,121 million in market capitalization and a tangible assets (inventory plus PP&E) to sales ratio of 0.956. 23.0 percent of our sample have their

⁸ We use pre-cleaned 10-K files provided by William McDonald at The Notre Dame Software Repository for Accounting and Finance (<https://sraf.nd.edu>). This data covers all SEC EDGAR 10-K filings and is pre-cleaned for easy access of 10-K text (all HTML formatting and tags, images, and tables are removed from the original SEC Edgar files). The data is currently updated for 1993–2018.

headquarters located in the western United States, and 12.0 percent of the sample belongs to the utility and banking industries. Our sample firms have a book-to-market ratio of 0.625, a leverage ratio of 0.232, a return on assets of -0.036, and annual returns of 1.133 percent. In addition, our sample firms have, on average, five operating segments and five geographic segments. Panel A also indicates that the mean number of words in a sample firm's 10-K is 53,405. This is similar to the overall market average (see Cazier and Pfeiffer 2016, Table 2).

Panel B of Table 1 presents descriptive statistics between firms that mention at least one wildfire in their 10-K filings (disclosers) and firms with no mentions (non-disclosers). The mean number of wildfire word count for disclosers is 2.622. Disclosers experience significantly more wildfire days in their headquarter counties relative to non-disclosers (3.873 versus 0.932 days, t -val. = 14.65). Disclosers are also larger (*MCAP*), more likely to be in the western regions (*WEST*) and the utility and banking industries (*UTILITY_BANKING*), and have more tangible assets (*TANGIBLE_ASSET*). As for the control variables, we observe that disclosers have higher leverage (*LEV*), more business segments (*LOG_B_SEG*), higher total word count in 10-Ks (*LOG_TOTAL_WORDCNT*), but lower return volatility (*RET_VOL*) and fewer numbers of geographic segments (*LOG_G_SEG*).

Table 2 presents descriptive statistics of the wildfire events (*WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT*) and wildfire disclosure (*WILDFIRE_WORDCNT* and *D_WILDFIRE_WORDCNT*) by state, industry, and year. Panel A summarizes descriptive statistics by state. We sort this table by the average number of wildfire days in a year. Hawaii, Oregon, and California are the top three states with the highest number of wildfire days. Firms in these three states experience an average of 10.9, 5.9, and 5.6 days of wildfire in their headquarter counties in a year (*WILDFIRE_DAYCNT*). Hawaii, California, and Idaho are the top three states with the largest

percentage of wildfire occurrence (*D_WILDFIRE_DAYCNT*). 78.5 percent, 39.2 percent, and 27.8 percent of firms in these three states experience at least one wildfire in their headquarter counties in a year. Hawaii, California, and Idaho also have the highest wildfire-related disclosure. For example, 8.8 percent, 4.5 percent, and 9.5 percent of firms in these three states mention at least one wildfire in its 10-K filings, respectively (*D_WILDFIRE_WORDCNT*). Finally, for each state, we report the number of total observations, the number of observations exposed to wildfire events, and the number of observations disclosed wildfire-related information in 10-Ks. We find that California, by far, has the most wildfire exposure and disclosure, and the top ten states ranked by the number of wildfire days are all in the western United States except for Florida. While the top nine western states count for 70.5 percent of the headquarters with wildfires in their county, this also implies that a significant portion of headquarters locates in non-western states. Thus, our sample is not confined geographically to one climatic region.

Panel B presents the wildfire events and wildfire disclosure by industry. Firms in the agriculture and forestry industry (SIC single digit=0) have the highest number of wildfire days, with an average of 2.9 days in a year (*WILDFIRE_DAYCNT*). Utility and transportation (SIC=4) have the most frequent mentions of wildfires in its 10-K filings (*WILDFIRE_WORDCNT*), followed by mining and construction (SIC=1), and finance, insurance and real estate (SIC=6).

Panel C shows the time trend of wildfire events and wildfire disclosure. While the number of wildfire days (*WILDFIRE_DAYCNT*) has fluctuated over time with peaks in 2002 (the Hayman Fire, Colorado Springs), 2003 (San Diego, the largest in CA at the time), and 2007, the number has increased significantly since 2016, largely due to the 2016 Chimney Tops fire in Gatlinburg TN, the 2017 Thomas Fire in CA, and the 2018 Mendocino Complex Fire in CA. Wildfire

disclosure has also increased rapidly in recent years. The percentage of wildfire disclosure firms (*D_WILDFIRE_WORDCNT*) increased from 0.3 percent in 1996 to 8.3 percent in 2018.

Table 3 presents the Pearson correlations among the variables. Notably, the number of wildfire-related words in firms' 10-Ks (*LOG_WILDFIRE_WORDCNT*) is positively associated with the number of wildfire days (*LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT*), and the variables associated with high wildfire risk: *LOG_MCAP*, *WEST*, *UTILITY_BANKING*, and *TANGIBLE_ASSET* (col. 1). *LOG_WILDFIRE_WORDCNT* is also positively associated with 10-K total word count (*LOG_TOTAL_WORDCNT*) (row 17). This suggests that temporal growth in the overall size of a 10-K filing partly explains changes in the wildfire word count. In addition, the wildfire exposure variables (*LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT*) are significantly associated with firms headquartered in the West (*WEST*) and have low correlations with the rest variables. These low correlations also substantiate that the wildfire events are more likely exogenous rather than influenced by outcomes linked to disclosure through correlated variables. This strengthens the formulation of our regression models.

3.3 Models

We specify two word-count models. The first regresses wildfire 10-K word count on wildfire exposure. Assuming that wildfire events are exogenous to disclosure behavior, this model examines the potential attribution of wildfire events to a subsequent change in wildfire 10-K disclosure. The model is:

$$\begin{aligned} LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 LOG_MCAP + \beta_3 WEST + \beta_4 \\ & UTILITY_BANKING + \beta_5 TANGIBLE_ASSET + \beta_6 BTM + \beta_7 LEV + \beta_8 ROA + \beta_9 RET + \beta_{10} \\ & RET_VOL + \beta_{11} LOG_G_SEG + \beta_{12} LOG_B_SEG + \beta_{13} LOG_TOTAL_WORDCNT + YEAR\ FIXED \\ & EFFECTS + INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \quad (1)$$

In this model, *LOG_WILDFIRE_WORDCNT* is defined as the natural log of one plus the total number of wildfire word count in 10-K filings for fiscal year *t*. *WILDFIRE_EVENT* is specified as

either the natural log of one plus the total number of days in a year with wildfires in a headquarter county (*LOG_WILDFIRE_DAYCNT*) or as an indicator variable for at least one wildfire event in a headquarter county (*D_WILDFIRE_DAYCNT*) for fiscal year t . We then control for firm size and several wildfire risk variables. *LOG_MCAP* measures the firm size and is the natural log of market capitalization for fiscal year t . *WEST* is an indicator variable that equals one for a firm headquarter located in a western state (i.e., AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, and WY), zero otherwise. *UTILITY_BANKING* is an indicator variable that equals one for firms in the utility and banking industries (SIC 4900 to 4999 and SIC 6000 to 6299 following Fama French 48 industry classifications), zero otherwise. *TANGIBLE_ASSET* is defined as inventory plus PP&E scaled by revenue at the end of year t . The other variables in Eq. (1) control for the determinants of 10-K disclosure commonly found in the broader literature (e.g., Bonsall et al. 2017; Campbell et al. 2014; Kravet and Muslu 2013; Li et al. 2013; Loughran et al. 2009). *BTM* is the book value of equity scaled by the market capitalization for fiscal year t . *LEV* is total debt scaled by total assets for fiscal year t . *ROA* is income before extraordinary items scaled by total assets for fiscal year t . *RET* is the annual return beginning nine months before to three months after fiscal year t . *RET_VOL* is the standard deviation of monthly returns over the fiscal year t . *LOG_G_SEG* and *LOG_B_SEG* are the natural log of one plus the number of geographic segments and business segments, respectively.

Finally, we include overall word count (*LOG_TOTAL_WORDCNT*), which is the natural log of one plus the number of total word count in 10-K filings. Given our first hypothesis, we expect to observe a significant positive coefficient for β_1 if firms increase wildfire disclosure as their wildfire exposure increases. However, β_1 could be insignificant if managers eschew disclosure of negative news, believe wildfire risk fails to meet the materiality threshold to disclose, prefer

boilerplate instead of specific language for negative events, or purchase insurance to partially cover wildfire risks.

The second model regresses wildfire 10-K word count on wildfire exposure, the partition variable for wildfire risk, and the interaction between the partition variable and wildfire exposure. We examine six different partition variables to investigate whether the coefficient for β_1 has increased in recent years, and is higher for firms that are larger, in the western United States, in the utility and banking industries, for firms with more tangible assets, and for firms that have experienced wildfire impacting their past operations. The model is:

$$\begin{aligned} LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 PARTITION + \beta_3 \\ & WILDFIRE_EVENT*PARTITION + \beta_4 BTM + \beta_5 LEV + \beta_6 ROA + \beta_7 RET + \beta_8 RET_VOL + \beta_9 \\ & LOG_G_SEG + \beta_{10} LOG_B_SEG + \beta_{11} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + \\ & INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it} \end{aligned} \quad (2)$$

The first partition variable is a two year-indicator capturing the sample periods of 2003–2008 and 2009–2018. *FY03_08* and *FY09_18* equal to one for observations in the two time periods, respectively, zero otherwise. We refer to 1996–2002 as the omitted group. We consider 2003–2008 a middle period where wildfire disclosure may have increased gradually due to the passage of Sarbanes Oxley Act which leads to an increase in risk factors disclosure (Dyer et al. 2017), and the issuance of the GAO environmental disclosure reports in 2004 and 2007. The 2004 report examined the issues of strategic environmental disclosures to determine ways the SEC could improve tracking and transparency of environmental information (GAO 2004). The 2007 report described the significance of climate change affecting future weather-related losses and identified financial risks to federal and private insurers (GAO 2007). We are particularly interested in the period after 2009 since it captures the year right before and the years after the SEC interpretative guidance that obliges climate change disclosure in 10-K filings (SEC 2010). We include the year 2009 as prior research suggests that firms proactively react to the SEC rule and implement the

disclosure early (Freedman et al. 2015). We exclude individual year fixed effects from this model. Given *H2a*, we expect positive coefficients for *WILDFIRE_EVENT*FY03_08*, and particularly for *WILDFIRE_EVENT*FY09_18*. This suggests that firms' wildfire 10-K disclosures are more responsive to the wildfire events in the middle and later periods versus the wildfire events in fiscal years 1996-2002.

The second variable is firm size (*LOG_MCAP*). We use an indicator version (*D_MCAP*) of *LOG_MCAP* to ease interpretation of the results. *D_MCAP* equals to one for firm-years with greater than annual median market capitalization, zero otherwise. *H2b* predicts that wildfire-exposed firms with larger sizes are likely to disclose more wildfire-related information since they cannot be exempted from the SEC climate risk disclosure release, and are under greater monitoring and scrutiny from investors and stakeholders. We expect a positive β_3 coefficient for *WILDFIRE_EVENT*D_MCAP*.

The third partition variable, *WEST*, is an indicator variable capturing firms headquartered in the western states. We predict that wildfire-exposed firms with their headquarters located in the western states are subject to higher wildfire risk due to the higher aridity in the west. We, therefore, expect a positive β_3 coefficient for *WILDFIRE_EVENT*WEST*.

The fourth partition variable is an indicator of utility and banking firms. (*UTILITY_BANKING*). Because utility and banking firms are naturally and contractually more exposed to wildfires, we predict that the level of textual wildfire disclosure in 10-K filings increases for these firms as the number of wildfire events in a county of the firm's headquarters increases. We expect a positive β_3 coefficient for *WILDFIRE_EVENT*UTILITY_BANKING*.

The fifth partition variable, *D_TANGIBLE_ASSET*, is an indicator version of *TANGIBLE_ASSET*. It measures the extent of tangible assets firms equip with. Since wildfire-exposed firms

with more tangible assets are more vulnerable to physical damages from the wildfires relative to similar firms with fewer tangible assets, we predict a positive β_3 coefficient for *WILDFIRE_EVENT*D_TANGIBLE_ASSET*.

Our last partition analysis uses two indicator variables capturing firms' wildfire disclosure location in 10-K filings. Specifically, *D_OTHER_ITEM* equals to one if firms disclose wildfire-related information in Items 2, 3, 6, 7, 7A, 8, 14, 15, the audit report, or the management internal control report of the 10-Ks, zero otherwise. We use *D_OTHER_ITEM* to capture firms that may have had wildfire events affecting their past operations. *D_ITEM1* equals to one if firms disclose wildfire-related information in Items 1, 1A, or the forward-looking statement only, zero otherwise. *D_ITEM1* likely captures firms with a general discussion of firms' wildfire risk. We predict a positive β_3 coefficient for *WILDFIRE_EVENT*D_OTHER_ITEM*. This suggests that wildfire-exposed firms with wildfire events affecting their past operations increase their level of wildfire disclosure as the number of wildfire events in a county of the firm's headquarters increases. The other variables are defined as before.

4 Results

4.1 10-K disclosure

Table 4 summarizes the results of estimating Eq. (1). This table indicates that firms located in a county with more wildfire days (col. 1) provide more textual disclosure of wildfire-related information in their 10-K filings in the year of the wildfires compared to firms exposed to fewer wildfire days (coeff. = 0.012, $p < 0.01$). Firms with at least one day of wildfire exposure (col. 2) also disclose more than firms without exposure to a wildfire in a year (coeff. = 0.021, $p < 0.01$). This suggests that wildfire-exposed firms are more likely to consider wildfire a material risk factor and disclose it in 10-K filings. This result also aligns with the increasing demand from investors

and stakeholders on wildfire-related information to better assess their risk portfolios. Our results further show that larger firms (*LOG_MCAP*) and firms with higher wildfire risk, that is, those in the western states (*WEST*), in the utility and banking industries (*UTILITY_BANKING*), and with a higher level of tangible assets (*TANGIBLE_ASSET*) also disclose more. Other control variables, mostly the common determinants of 10-K disclosure suggested by the prior literature, are not significantly associated with wildfire disclosure. The only significant variables are book-to-market ratio and total 10-K word count, both of which positively and significantly associate with wildfire word count.

We interpret the economic significance of the coefficient for *LOG_WILDFIRE_DAYCNT* from col. 1 of Table 4 as follows. An increase in the number of wildfire days from 0 to 3, which is the average number of days in 2018, increases the average number of wildfire word count by 50 percent. Mathematically, given the coefficient of 0.012 in col. 1, $\log(1+WILDFIRE_WORDCNT(day=3))$ minus $\log(1+WILDFIRE_WORDCNT(day=0))$ equals $0.012 * [\log(1+3) - \log(1+0)]$. This equation can be simplified to the ratio of $(1+WILDFIRE_WORDCNT(day=3))$ to $(1+WILDFIRE_WORDCNT(day=0))$ equaling $[(1+3)/(1+0)]^{0.012}$ which is 1.016. This means that *WILDFIRE_WORDCNT* (*day=3*) equals to $0.0167 + 1.0167 * WILDFIRE_DAYCNT(day=0)$ after rearranging. Since the mean value of *WILDFIRE_WORDCNT* for *day=0* is 0.034 from our sample, the implied mean value of *WILDFIRE_WORDCNT* for *day=3* is 0.051 or $(0.0167 + 1.0167 * 0.034)$, or a 50 percent increase from the mean value of *day=0* of $[(0.51 - 0.34)/0.34]$. For this interpretation, we use the increase of the number of days from 0 to 3. The effect is not linear, so that the impact of disclosure from an increase of 0 to 3 days is not the same as an increase of 3 to 6 days.

4.2 Trend analysis

Table 5 presents the results of regressing wildfire disclosure on wildfire events over time. Cols. 1 and 2 use *LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT* as the measure of wildfire events, respectively. In col. 1, the coefficient for *LOG_WILDFIRE_DAYCNT*FY03_08* is 0.012 and significant ($p < 0.01$). This indicates an increase in the sensitivity of 10-K disclosure to wildfire events in the 2003–2008 period relative to the earlier period. This coefficient also exceeds the unconditional coefficient for *LOG_WILDFIRE_DAYCNT* with a net effect of 0.008 ($-0.006 + 0.012$). In other words, in the period of 2003–2008, firms located in a county with more wildfire days provide more textual disclosure of wildfire-related information in their 10-K filings in response to a higher level of wildfire exposure. This result is consistent with the increasing demand for risk and climate change disclosure after the SOX and GAO reports.

Finally, the coefficient for *LOG_WILDFIRE_DAYCNT* FY09_18* is 0.037 and significant ($p < 0.01$). This suggests that there is also an increase in the sensitivity of wildfire 10-K disclosure to wildfire events in the 2009–2018 period relative to the 1996–2002 period. This increase in the later period of our sample is much larger with a net effect of 0.031 ($-0.006 + 0.037$). This indicates that the level of wildfire disclosure in more recent years rises more as the number of wildfire exposure days increases. This result is consistent with greater public awareness of wildfire impacts in recent years and the SEC’s 2010 guidance release on climate change disclosure in 10-K filings. The results in col. 2 of Table 5 using *D_WILDFIRE_DAYCNT* as the wildfire exposure measure are similar to those in col. 1 of Table 5. Overall, these results support *H2a*.

4.3 Larger firms

Table 6 presents the results on the impact of larger firms (*D_MCAP*) on the positive relation between wildfire exposure and wildfire disclosure. Similar to Table 5, we measure wildfire events

using the number of wildfire days (col. 1), and an indicator for the wildfire occurrence (col. 2). Table 6 indicates that the coefficients for $LOG_WILDFIRE_DAYCNT*D_MCAP$ and $D_WILDFIRE_DAYCNT*D_MCAP$, of 0.020 and 0.036, respectively, are significantly positive. This suggests that when firms are larger, and thus are subject to more public scrutiny or cannot be exempted from the SEC's disclosure obligations, the level of wildfire disclosure in 10-K filings increases as the number of wildfire events in the county of the firm's headquarter increases. The coefficients for $LOG_WILDFIRE_DAYCNT$ and $D_WILDFIRE_DAYCNT$ alone are small and insignificant. This suggests that for smaller firms the relation between wildfire exposure and disclosure is limited. Taken together, the results in this table support *H2b*.

4.4 Firms in the West

Table 7 tests whether the wildfire-related 10-K disclosure of firms in the West is more responsive to wildfire events than firms located elsewhere. Our state fixed effect in this model includes all states except for the western states. We find support for this proposition. First, the coefficients for *WEST* in cols. 1 and 2 are both positive and significant ($p < 0.01$), indicating that firms in the west disclose more wildfire-related information in the 10-Ks, on average. Second, we observe a positive coefficient for $LOG_WILDFIRE_DAYCNT*WEST$ (0.012, $p < 0.01$) (col. 1) and a positive coefficient for $D_WILDFIRE_DAYCNT*WEST$ (0.029, $p < 0.01$) (col. 2). Hence, western US firms not only disclose significantly more wildfire information in their 10-Ks, but also, those 10-K wildfire-related disclosures vary positively by the number of wildfire days in the firm's headquarter county.

4.5 Utility and banking firms

Utility and banking firms are naturally and contractually more exposed to wildfires. Table 8 summarizes the results focusing on these two industries. Our industry fixed effect in this model

includes all industries but utility and banking. The table documents that the interaction coefficient for *LOG_WILDFIRE_DAYCNT*UTILITY_BANKING* is 0.063 and significant ($p<0.05$) and the coefficient for *D_WILDFIRE_DAYCNT*UTILITY_BANKING* is 0.116 and significant ($p<0.05$). Therefore, for these industries, the level of wildfire disclosure in 10-K filings increases as the number of wildfire events in a county of the firm's headquarter increases.

4.6 Firms with large tangible assets

Wildfire-exposed firms with large tangible assets are likely to suffer more physical damages when wildfires hit. We, therefore, predict that these firms will disclose more wildfire-related information given their higher wildfire risk than similar firms with smaller tangible assets. Table 9 offers support for our prediction. We interact wildfire events variables with an indicator of higher than median tangible assets (*D_TANGIBLE_ASSET*) and find that the coefficients for *LOG_WILDFIRE_DAYCNT* D_TANGIBLE_ASSET* in col. 1 and *D_WILDFIRE_DAYCNT*D_TANGIBLE_ASSET* in col. 2 are both significantly positive ($p<0.01$). This result suggests for firms with high tangibles assets, the level of wildfire disclosure in 10-K filings increases as the number of wildfire events in a county of the firm's headquarter increases.

4.7 Firms with wildfire events affecting past operations

We next examine whether the 10-K disclosures of wildfire-exposed firms vary by firms' wildfire activities in the past. We use the disclosure location in firms' 10-K filings to measure the differing impact of wildfire cost and risk faced by the firms. Panel A of Table 10 reports the number of mentions by item number. For example, under col. *N*, the 1,121 Item 1A risk factor mentions indicates that 1,121 firm-year observations in our sample mention wildfire at least once in Item 1A. Overall, we observe that 68.8 percent of the firm-year observations $((53+280+1,121)/2,113)$ mention wildfire at least once in a Forward-looking statement and an Item

1 (describes the business) or Item 1A (discusses the risk factors) disclosure. Also, 14.4 percent of the firm-year observations (305/2,113) mention wildfire in other items. As such, the percentage of firms with wildfire mentions in these three categories only (*D_ITEM1*) is 54.1 percent (1,143/2,113). We argue that these firms are more likely than others to consider wildfire risk as a material risk factor but have likely not had wildfires affecting their past operations. By contrast, firms that mention wildfires at least once in other items such as legal proceedings, financial statements, and exhibits and tables (*D_OTHER_ITEM*) represent 31.2 percent (659/2,113) of the discloser sample. These firms likely have experienced wildfire events that affected their businesses and, thus, discussed the impact in various other sections of the 10-K filings. Col. *D_ITEM1&7* is similar to col. *D_ITEM1*, except that Col. *D_ITEM1&7* groups Item 7 MD&A and Item 7A market risk disclosure with the Item 1 and Item 1A mentions, assuming that Items 7 and 7A are also used to capture firms' general descriptions of wildfire risk. *D_OTHER_ITEM2* is similar to *D_OTHER_ITEM* except that it excludes Items 7 and 7A. Panel B summarizes the number of 10-K mentions by the item number of the disclosure location. For a total of 2,113 location mentions, 1,268 firm-years mention wildfire at least once in an item, 192 firm-years mention wildfire in two items, and so forth. There is one firm that mentions wildfire in eight disclosure items.

Panel A of Table 11 presents the results of Eq. (2f), which regresses wildfire disclosure on wildfire events, indicators for the two disclosure locations, and their interactions. Cols. 1 and 2 use *LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT* as the measure of wildfire events, respectively. In both columns, the coefficients for *D_ITEM1* and *D_OTHER_ITEM* are significantly positive. This indicates by construction of the variables that firms that disclose in either item category have a higher wildfire word count in 10-K filings than firms without any mentions of wildfires. When we interact the wildfire event variables with *D_ITEM1* and

D_OTHER_ITEM, respectively, we find that the coefficient for the interaction with *D_ITEM1* is not significant, but that the interaction with *D_OTHER_ITEM* is significantly positive. This is interesting, as it suggests that for wildfire-exposed firms that have likely experienced wildfires affecting their past operations (and, thus, they discussed wildfires in Items 2, 3, 6, 7, 7A, 8, 14, 15, the audit report, or the management internal control report), their overall sensitivity of wildfire-related disclosure to wildfire events is significantly higher.

Item 7–MD&A and Item 7A–qualitative and qualitative disclosures about market risk have a less clear indication of firms’ wildfire impact relating to the past. We, therefore, modify the definition of *D_ITEM1* to include Items 7 and 7A in the group representing the general discussion of firms’ wildfire risk. We name this new variable *D_ITEM1&7*. We then redefine *D_OTHER_ITEM2* excluding Items 7 and 7A. We find consistent results that wildfire-exposed firms that discuss wildfires in Items 2, 3, 6, 8, 14, 15, the audit report, or the management internal control report have an overall greater amount of wildfire disclosure in their 10-Ks. As shown in Panel B of Table 11, the coefficients for the interaction variables with *D_OTHER_ITEM2* are significantly positive (col. 1, $p < 0.01$; col. 2, $p < 0.05$), but the coefficients for the interaction variables with *D_ITEM1&7* are not significant.

4.8 Difference-in-differences model

We address the concern that unobservable time-invariant differences between the treatment sample (firms exposed to wildfire) and the control sample (otherwise equivalent firms not exposed to wildfire as defined below) could affect the relation between wildfire exposure and disclosure. We specify a difference-in-differences (DiD) model following related prior work (e.g., Bertrand and Mullainathan 2003; Kim and Klein 2017). First, for each firm, we divide the sample period into a wildfire-transition period (year t), a pre-wildfire period (year $t-1$), and a post-wildfire period

(year $t+1$). We define the wildfire-transition period as the year when a firm shifts from a non-wildfire period (of no wildfire days) ($WILDFIRE_DAYCNT=0$) to a period of one or more wildfire days ($WILDFIRE_DAYCNT>0$). We require that each wildfire period lasts for at least two years, and that no wildfire occurs in the headquarter county of each firm for at least two years before the wildfire event. Second, a firm may have multiple transition, pre, and post-wildfire periods throughout our sample period. In this case, we treat non-consecutive wildfires as separate events. These two requirements generate a sample of 740 distinct treatment firms for our DiD analysis: 599 firms appear once in the treatment sample, 92 firms appear twice, and 49 firms appear three times. Third, we define *TREAT* as an indicator variable that equals 1 for wildfire-affected firms, and 0 for firms that experience no wildfire event from year $t-1$ to $t+1$. Fourth, we select for each treatment firm a control firm that is not exposed to wildfires in its headquarter county in the sample period, but is of similar market capitalization and in the same industry (SIC 2 digit) and year as the exposure (treatment) firm. We define *POST* an indicator variable that equals to 1 for the post-wildfire period and 0 for the pre-wildfire period. Thus, the transition year is excluded in this analysis. Based on the preceding definitions of *TREAT* and *POST*, we estimate the following DiD model:

$$LOG_WILDFIRE_WORDCNT = \alpha_0 + \beta_1 TREAT + \beta_2 POST + \beta_3 TREAT*POST + CONTROLS + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it} \quad (3)$$

Eq. (3) includes the same control variables and the same year, industry, and state fixed effects as per Eq. (1).

Table 12 summarizes the results of estimating Eq. (3). The coefficient for *TREAT* (col. 1) is insignificant (coeff. = 0.011, $p>0.10$). This indicates that treatment firms do not exhibit significantly higher wildfire disclosure in the pre-wildfire period compared to control firms. By contrast, the coefficient for *TREAT*POST* (col. 1) is significantly positive (coeff. = 0.017, $p<0.05$).

This indicates that treatment firms have a significantly higher sensitivity of wildfire disclosure (based on word count) to wildfire days in the post-wildfire period compared to control firms that do not have any wildfire exposure.

Fig. 1 plots the change in wildfire disclosure from the pre- to the post-period for the treatment sample and the control sample based on the coefficients from estimating Eq. (3) in Table 12. The *TREAT* coefficient increases from 0.011 (*t*-stat. = 1.51) to 0.028 (*t*-stat. 3.05) (0.028 = the *TREAT* coefficient of 0.011 plus the coefficient for the interaction term of *TREAT*POST* = 0.017). We also check for parallel trends prior to the wildfire shock. This is an identifying assumption central to a causal interpretation of the DiD specification. Figure 2 plots the mean values of *LOG_WILDFIRE_WORDCNT* from year *t*-2 to year *t*+1 where year *t* is the transition year. The pre-treatment trends (i.e., the slope from year *t*-2 to year *t*-1) of these two groups are clearly visible and similar (i.e., parallel). Together, the significant coefficient for *TREAT*POST* in Table 11 and the parallel trends indication in Fig. 2 confirm that our main findings (Tables 4–9, 11) are unlikely to be driven by unobservable time-invariant variables.

4.9 Firm fixed effects model

Another way to check if time-invariant omitted firm characteristics affect our main findings is to estimate a firm fixed effects model. We, therefore, include firm fixed effects in our baseline model (Eq. 1) and re-estimate the regressions in Table 4. Untabulated results show that *LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT* are significantly and positively associated with *LOG_WILDFIRE_WORDCNT* for *LOG_WILDFIRE_DAYCNT* (coeff. = 0.002, *p*<0.05) and *D_WILDFIRE_DAYCNT* (coeff. = 0.003, *p*<0.10). As such, within firms and throughout our sample period, wildfire disclosure is significantly higher in years when firms are exposed to more wildfire days than in years when they are exposed fewer or no wildfire days.

5 Additional Analyses

5.1 Weighted average measure of wildfire risk

We measure a firm's wildfire risk exposure using the number of wildfire days in a year in the firm's headquarter county. A limitation of this measure is that a firm may have operations with wildfire exposure outside of its headquarter county. To mitigate this issue, we calculate the weighted-average number of wildfire days that incorporates a firm's operations across multiple states. Following García and Norli (2012), we first count the occurrence of state names in Item 1: Business, Item 2: Properties, Item 6: Consolidated Financial Data, and Item 7: Management's Discussion and Analysis in a firm's 10-K. We then calculate the number of wildfire days in a year for each mentioned state. Finally, for each firm-year, we calculate a weighted average measure using the number of wildfire days in all mentioned states weighted by the number of mentions. For example, Intel has its headquarter in California. In its 2008 10-K, it mentioned California (4 times), Oregon (3 times), Arizona (2 times), New Mexico (1 time), and Massachusetts (1 time) in the four Items of the 10-K mentioned above. The numbers of wildfire days for these five states are 145, 87, 0, 36, and 0, respectively. The weighted measure is, therefore, calculated as $145 \times 4/11 + 87 \times 3/11 + 0 \times 2/11 + 36 \times 1/11 + 0 \times 1/11$, which equals to 79.73 days.⁹ This measure is more comprehensive in reflecting firms' wildfire risk exposure as it allows wildfire risk exposure to vary across firms based on the locations of their operations rather than solely on headquarter

⁹ In 2008, Intel had several facilities in California. It also had its manufacturing sites in Albuquerque, New Mexico; Chandler, Arizona; and Hillsboro, Oregon; R&D centers in Austin, Texas and Hudson, Massachusetts; and design centers in Fort Collins and Longmont, Colorado. Our 2008 searches pick up 5 out of 7 states (Texas and Colorado were not mentioned). Texas and Colorado were mentioned in other years, for example, over our sample period of 1996 to 2018, Intel's 10-K mentioned California (63 times), Oregon (62), Arizona (61), New Mexico (33), Massachusetts (30), Colorado (17), and Texas (9) in items 1, 2, 6 and 7 of 10-Ks.

location. The descriptive of this weighted average shows that, at the firm-year level, the mean and the median number of states mentioned in the four sections of 10-Ks are 7.66 and 6, respectively.¹⁰ Table 13 presents the regression results for Eq. (4) using a sample of firms with at least one state mention in their 10-Ks. Col. 1 uses a continuous wildfire exposure variable (*LOG_WEIGHTED_DAYCNT*). Col. 2 uses a dummy variable that equals 1 if the weighted average number of wildfire days is greater than the sample median, and 0 otherwise (*D_WEIGHTED_DAYCNT*). The positive and significant coefficients for the wildfire variables in both columns indicate that firms with high wildfire risk affecting their operations disclose more wildfire-related information. Hence, our results based on headquarter counties do not change under this alternative definition.

5.2 Headquarter concentration

A second way to complement the use of headquarter county is to use a headquarter concentration ratio. Specifically, we calculate the headquarter concentration ratio in each headquarter state as the ratio of the number of Item 1, 2, 6, and 7 mentions of the headquarter state relative to all states mentioned in the 10-K. This measure ranges from 0 (the firm has no operations in its headquarter state) to 1 (the firm has all of its operations in the headquarter state). We then define an indicator variable for headquarter concentration ratio (*HIGH_CONCEN*) equals to 1 when the ratio exceeds 0.50, and 0 otherwise. In our sample, 32.9 percent of firms have more than 50 percent of their operations in the headquarter state. Table 14 presents the results of regressing wildfire disclosure on wildfire events and their interaction with high headquarter concentration (Eq. (5)). The coefficients for the interaction variables *LOG_WILDFIRE_DAYCNT**

¹⁰ This measure also has the added advantage that helps address the concern of a potential selection bias from the use of headquarter location because firms choose their headquarter location. Using the diversity of states as the basis for location identification helps reduce this bias.

HIGH_CONCEN (col.1) and *D_WILDFIRE_DAYCNT*HIGH_CONCEN* (col. 2) are both significantly positive. This suggests that the positive relation between wildfire exposure and disclosure is more pronounced for firms with more concentrated operations in the headquarter state. In other words, a firm with wildfire days in a headquarter state with a high concentration of operations in the headquarter state location associates with a higher level of wildfire disclosure.

5.3 Insurance coverage

Some firms may have access to wildfire risk insurance. Most insurance firms, however, do not cover wildfires as a whole because of amount of damage that occurs when one happens is largely unknowable. Some insurance companies may even refuse coverage by specifically excluding wildfires when writing policies or pulling out altogether from providing coverage in wildfire-prone areas they deem too risky to insure. Whether a firm has wildfire coverage and the extent of the coverage could moderate the positive relation between wildfire exposure and wildfire disclosure. With more coverage, a firm may have less need to disclose wildfire-related information in its 10-K. Ideally, we would like to identify the insurance coverage for our wildfire sample. However, firms rarely disclose their insurance policies and the extent of the coverage. We, therefore, use an indirect approach to explore the potential impact of insurance coverage on our main relation. Specifically, we identify all wildfire episodes during our sample period from NOAA. An episode contains multiple wildfire events that occur during the same time period and at nearby counties/zones. We then run an event study on the insurance companies (310 firms with 2,751 firm-year observations in our sample) around the wildfire events. If the cumulative abnormal return (*CAR*) around the wildfire events is significantly negative for this sample, then this is prima facie evidence that covered wildfire firms are using their coverage to recoup losses (Angbazo and Narayanan 1996; Lamb 1998). We can then include the negative *CAR* of insurance companies in

the disclosure regression to control for the effect of insurance coverage on wildfire disclosure. If we observe no significantly negative response around the events, then we can reasonably conclude that insurance coverage is unlikely to drive wildfire disclosure. Insurance companies may increase rates, however, but these are uncertain at the time of a wildfire event and must be approved at the state level.

We present the Fama-French four-factor *CAR* and a value-weighted market-adjusted *CAR* around the wildfire events in Table 15. We examine three windows: *CAR0* (the event date), *CAR7* (the event date plus seven trading days), and *CAR30* (the event date plus thirty trading days). Panel A reports the results at the country level, where we examine the *CAR* of insurance companies in all states based on all wildfire episodes in our sample period. We find that the Fama-French four-factor *CAR* is significantly positive for *CAR0* and *CAR30*, and significantly negative for *CAR7*. However, the economic significance of these results is very small. The mean *CAR* values are 0.012 percent, -0.023 percent, and 0.049 percent for *CAR0*, *CAR7*, and *CAR30*, respectively. The market-adjusted *CARs* are all significantly positive during the wildfire episode periods. The mean values are 0.155 percent, 0.349 percent, 1.041 percent for *CAR0*, *CAR7*, and *CAR30*, respectively.

Panel B of Table 15 presents the results at the region level. Here we examine the impact of wildfire episodes in each of the five regions on the stock returns of the insurance companies in the same region. We, therefore, assume that wildfire firms likely purchase insurance from an insurance company in the same region, and thus the stock returns of insurance companies in the same region should be negatively affected when local wildfires occur. We find that both Fama-French *CAR* and market-adjusted *CARs* are all significantly positive in the wildfire event windows. Again, the economic significance of the *CARs* is small. Finally, Panel C presents the results at the state level. Here, we assume that wildfire firms purchase their insurance from an insurance company in the

same state and, thus, the stock returns of insurance companies in the same state should be negatively affected when local wildfires occur. Panel C shows that the *CARs* for the insurance companies conditional the wildfire exposure in the same states are mixed. Overall, our analysis provides no consistent evidence that investors react significantly negatively to insurance stocks given wildfire events. As such, we offer no compelling evidence to support the view that wildfire firms use insurance coverage to mitigate their wildfire costs that could, in turn, shape their wildfire disclosure.¹¹

5.4 Metropolitan statistical area (MSA)

In the main analysis, we focus on wildfire events in the same county of the company's headquarters, that is, we assume that the wildfire risk should be highest when wildfires occur in close proximity to the company. Firms could also perceive high wildfire risk when their neighbor counties experience a wildfire event. We, therefore, perform two tests to understand how wildfire events firms' wildfire disclosure at the MSA level. First, we examine the extent to which wildfire events occurring in the same MSA of the firm's headquarters affect wildfire-related 10-K disclosure. We obtain the MSA and county link table from the US Census Bureau. Our sample consists of 237 MSAs covering 837 counties. An untabulated analysis finds significant results similar to those of the main analysis (Tables 4–9, 11). However, because the coefficients for *LOG_WILDFIRE_DAYCNT* and *D_WILDFIRE_DAYCNT* are slightly smaller, the economic significance of the wildfire impact drops slightly. Second, we examine if firms located next to the wildfire county (i.e., in the same MSA but not in the wildfire county) have more or less wildfire-

¹¹ In an untabulated analysis, we find that the *CARs* around the wildfire event dates of firms that disclose wildfire-related information in their 10-K (wildfire disclosers) are significantly more negative than those that do not disclose. This suggests that the *act* of disclosure of wildfire information in a 10-K makes a difference. One reason for the difference is that wildfire discloser firms disclose material information. Material information, by definition, is expected to be price-sensitive information for an outside investor.

related disclosure than firms located in the wildfire county. We modify our main variable of interest, *LOG_WILDFIRE_DAYCNT*, into two variables: *LOG_WILDFIRE_DAYCNT_SAME* and *LOG_WILDFIRE_DAYCNT_NEIGHBOR*. *LOG_WILDFIRE_DAYCNT_SAME* equals to *LOG_WILDFIRE_DAYCNT* if a firm experiences wildfire in its headquarter county, and 0 otherwise. *LOG_WILDFIRE_DAYCNT_NEIGHBOR* equals to *LOG_WILDFIRE_DAYCNT* if a firm experiences wildfire in its MSA but not in its headquarter county, and 0 otherwise. Table 16 shows the results of estimating Eq. (6). The coefficients for *LOG_WILDFIRE_DAYCNT_SAME* and *LOG_WILDFIRE_DAYCNT_NEIGHBOR* are 0.009 ($p < 0.01$) and 0.004 ($p < 0.05$), respectively. This suggests that wildfire events affect the disclosure of firms headquartered in the event county as well as firms headquartered in the neighbor counties. An F-test between these two coefficients suggests that the coefficient for *LOG_WILDFIRE_DAYCNT_SAME* is significantly greater than that for *LOG_WILDFIRE_DAYCNT_NEIGHBOR* (F-stat = 6.28, p-val = 0.012). This suggests that wildfire events affect the disclosure of firms in the same county of the events more than their effect on the disclosure of firms in the neighboring counties.

5.5 Falsification test

To support further our main finding that firms' sensitivity of disclosure of wildfire-related information relates causally to their level of exposure to wildfire days, we perform a falsification test, also based on location. We focus on the subsample of firms in the wildfire sample with high foreign operations defined as those firm-years with more than 50 percent of pre-tax income attributable to foreign operations. Consistent with our expectation, an untabulated analysis of the wildfire subsample indicates negative coefficients for *LOG_WILDFIRE_DAYCNT* (coeff. = -0.005, t stat. = -1.26) and *D_WILDFIRE_DAYCNT* (coeff. = -0.009, t stat. = -1.27). This suggests that when firms have a majority of their operations in overseas locations they are less

subject to the wildfire risk. As such, the wildfire-related information in their 10-Ks, if any, is not responsive to the number of wildfire days in the county of their headquarters.

5.6 Using an indicator of wildfire disclosure as the dependent variable

Our main analysis uses the word count of wildfire mentions as the dependent variable to capture the extent of wildfire-related disclosure. As a sensitivity test, we repeat the analysis by replacing the word count variable with an indicator variable for the incident of disclosure (*D_WILDFIRE_WORDCNT*). Untabulated results from logistic regressions show that firms with greater wildfire exposure are more likely to disclose wildfire-related information in their 10-Ks.

6 Conclusion

Wildfires have been omnipresent in the United States since record-keeping began. Yet, today, more acreage burns and the fire season has lengthened and increased in severity (Abatzoglou and Williams 2016; Cook et al. 2004; Goss et al. 2020). Optimal strategies to manage and mitigate wildfire risk at the macro level pose substantial challenges for policymakers. Importantly, the private sector is not immune to this emerging risk. In this paper, we provide some of the first evidence on how wildfire occurrences relate to information relevant to firm value. Specifically, we use geospatial data on wildfire exposure at the county level to explore whether US firms' 10-Ks reflect the threat or risk of firms' exposure to wildfires.

As our main finding, we present evidence that supports affirmatively our research question at the outset. Firms experiencing more wildfire days in a year disclose more wildfire information in their annual 10-Ks on average. Firms experiencing fewer wildfire days disclose less. Wildfire-exposed firms' disclosures have increased significantly in recent years and are mostly explained by larger firms. Moreover, those wildfire-exposed firms with heightened wildfire concerns—in the western US regions, in the utility and banking industries, with high tangible assets, and likely to

have had wildfire events affecting firms' past operations—disclose more. Our evidence points to the recognition of wildfire exposure in firms' 10-K disclosures as a significant risk factor for financial reporting as a relatively new phenomenon.

While our research design uses geospatial variation in exogenous events as an identification strategy to establish a causal connection, our analysis does not identify a precise mechanism whereby the exogenous events link to firms' outcomes of disclosure. Since our study is largely exploratory on a topic that is noticeably understudied in the accounting and finance literatures, there is much scope for additional cross-disciplinary research in this area. This research could build on the fire and weather science literatures. Extensions of the current work are underway on two related topics: when and how equity and credit market prices might respond to one or more of wildfire events and 10-K textual disclosures of those events, and when and how external auditors and financial analysts might respond to wildfire events and disclosures. Future studies could also explore the patterns of more complex disclosure measures for wildfires and wildfire disclosure through other channels (e.g., 8-K, 10-Q, sustainability reports).

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Appendix 1. Wildfire Distribution by County

Panel A: By County

Panel B: By County with Firm Headquarter Data in Our Sample

Panel C: By County with the Number of Wildfire Days 1996–2018

Panel D: By County with the Number of Wildfire Days: 1996–2008 versus 2009–2018

This appendix presents three maps capturing the distribution of wildfire by county. Panel A presents the wildfire distribution by county. Panel B presents the wildfire distribution for counties with headquarters in our sample. Panel C presents the number of wildfire day counts in each county. Panel D maps the number of wildfire days by county for 1996–2008 and 2009–2018.

Appendix 2. Wildfire-Related Disclosure in 10-Ks

Example 1. Excerpts from PG&E 2016 10-K (8 mentions of wildfire)

Item 1. Business/Environmental regulation/Climate change mitigation and adaption strategies (page 21)

The Utility regularly reviews the most relevant scientific literature on climate change such as sea level rise, temperature changes, rainfall and runoff patterns, and **wildfire** risk, to help the Utility identify and evaluate climate change-related risks and develop the necessary adaptation strategies. The Utility maintains emergency response plans and procedures to address a range of near-term risks, including extreme storms, heat waves and **wildfires** and uses its risk-assessment process to prioritize infrastructure investments for longer-term risks associated with climate change.

The Utility's vegetation management activities also reduce the risk of **wildfire** impacts on electric and gas facilities.

Item 1A. Risk factors/risks related to operations and information technology (page 29)

The Utility may incur material liability in connection with a **wildfire** (known as the "Butte fire") that ignited and spread in Amador and Calaveras counties in Northern California in September 2015 depending on the outcome of the investigations into the cause of the fire. If insurance recoveries are unavailable or insufficient to cover such costs, PG&E Corporation's and the Utility's financial condition or results of operations could be materially affected. The Utility also could incur material fines, penalties or disallowances, as a result of enforcement actions taken by the CPUC or other law enforcement agencies.

Item 1A. Risk factors/risks related to environmental factors (page 31)

In addition, increasing temperatures and lower levels of precipitation could increase the occurrence of **wildfires** in the Utility's service territory causing damage to the Utility's facilities or the facilities of third parties on which the Utility relies to provide service, damage to third parties for loss of property, personal injury, or loss of life

Item 3. Legal proceedings/Investigation of the Butte Fire

In September 2015, a **wildfire** (known as the "Butte fire") ignited and spread in Amador and Calaveras Counties in Northern California. The California Department of Forestry and Fire Protection ("Cal Fire") is investigating the source of the Butte Fire to determine whether a tree contacted a power line operated by the Utility and was the cause of the fire. Cal Fire has reported that as a result of the fire there were two deaths and 965 structures, including 571 houses, were damaged or destroyed. Cal Fire's investigation is expected to conclude in 2016.

Item 7. Management Discussion and Analysis of Financial Condition and results of operations/Cautionary language regarding forward-looking statements

The impact of droughts or other weather-related conditions or events, **wildfires** (such as the Butte fire), climate change, natural disasters, acts of terrorism, war, or vandalism (including cyber-attacks), and other events, that can cause unplanned outages, reduce generating output, disrupt the Utility's service to customers, or damage or disrupt the facilities, operations, or information technology and systems owned by the Utility, its customers, or third parties on which the Utility relies; whether the Utility incurs liability to third parties for property damage or personal injury caused by such events; and whether the Utility is subject to civil, criminal, or regulatory penalties in connection with such events;

Item 8. Financial statements and supplementary data / Note 13: Contingencies and Commitments/Investigation of the Butte Fire (page 123)

In September 2015, a **wildfire** (known as the "Butte fire") ignited and spread in Amador and Calaveras Counties in Northern California. The California Department of Forestry and Fire Protection ("Cal Fire") is

investigating the source of the Butte Fire to determine whether a tree contacted a power line operated by the Utility and was the cause of the fire. Cal Fire has reported that as a result of the fire there were two deaths and 965 structures, including 571 houses, were damaged or destroyed. Cal Fire's investigation is expected to conclude in 2016.

Example 2. Excerpt from Cincinnati Financial Corporation 2016 10K (2 mentions)

Item 1A. Risk factors (page 30)

We could experience an unusually high level of losses due to catastrophic, terrorism or pandemic events or risk concentrations. In the normal course of our business, both in our insurance and reinsurance operations, we provide coverage against perils for which estimates of losses are highly uncertain, in particular catastrophic and terrorism events. Catastrophes can be man-made or caused by natural perils. Man-made catastrophes to which we may be exposed include, but are not limited to, industrial accidents, terrorist attacks, social unrest and riot. Natural peril catastrophe events to which we may be exposed include, but are not limited to, hurricanes, tornadoes, windstorms, earthquakes, landslides, hailstorms, flooding, severe winter weather and **wildfires**. Due to the nature of these events, we are unable to predict precisely the frequency or potential cost of catastrophe occurrences. Various scientists and other experts believe that changing climate conditions have added to the unpredictability, frequency and severity of such natural disasters in certain parts of the world and have created additional uncertainty as to future trends and exposures. We cannot predict the impact that changing climate conditions may have on our results of operations nor can we predict how any legal, regulatory or social responses to concerns about climate change may impact our business. Additionally, man-made events, such as hydraulic fracturing, could cause damage from earth movement or create environmental and/or health hazards.

The geographic regions in which we market insurance and reinsurance are exposed to numerous natural catastrophes, such as:

- Hurricanes in the gulf, eastern, southeastern and northeastern coastal regions.
- Earthquakes in many regions, most particularly in the New Madrid fault zone, which lies within the central Mississippi valley, extending from northeast Arkansas through southeast Missouri, western Tennessee and western Kentucky to southern Illinois, southern Indiana and parts of Ohio.
- Tornado, wind and hail in the Midwest, South, Southeast, Southwest and the mid-Atlantic.
- **Wildfires.**
- On a worldwide basis, in the event of a severe catastrophic event or terrorist attack we may be exposed to material losses through our reinsurance assumed operations.

Appendix 3. Variable Definitions

Variables	Definition	Source
Main Dependent Variables		
$LOG_WILDFIRE_WORDCNT_{it}$	Natural logarithm of one plus total word count of "wildfire" or "wild fire" in firm i 's 10-K filing for fiscal year t ;	SEC Edgar
$D_WILDFIRE_WORDCNT_{it}$	1 if firm i mentions at least one "wildfire" or "wild fire" in the 10-K filing for fiscal year t , 0 otherwise;	SEC Edgar
$LOG_WILDFIRE_DAYCNT_{it}$	Natural logarithm of one plus the total number of days with a wildfire event in firm i 's headquarter county for fiscal year t ;	Nat. Oceanic & Atmospheric Admin. (NOAA)
$D_WILDFIRE_DAYCNT_{it}$	1 if firm i 's headquarter county encounters at least one wildfire event for fiscal year t , 0 otherwise;	NOAA
Main Independent Variables		
$FY03_08$	1 for the sample period between 2003 and 2008, 0 otherwise;	Compustat
$FY09_18$	1 for the sample period between 2009 and 2018, 0 otherwise;	Compustat
LOG_MCAP_{it}	Natural logarithm of market capitalization ($csho \times prcc_f$) for firm i as of fiscal year t 's year-end;	Compustat
D_MCAP_{it}	1 if firm i 's market capitalization is greater than the annual median, 0 otherwise;	Compustat
$WEST_{it}$	1 if firm i 's headquarter is located in states AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, WY, 0 otherwise;	Compustat
$UTILITY_BANKING_{it}$	1 if firm i is in the utility or banking industries (SIC 4900 to 4999 or 6000 to 6299 following Fama French 48 industry classifications), 0 otherwise;	Compustat
$TANGIBLE_ASSET_{it}$	Firm i 's inventory and property, plant, and equipment ($invnt+ppeg$) divided by revenue (rev) for fiscal year t ;	Compustat
$D_TANGIBLE_ASSET_{it}$	1 if firm i 's tangible asset is greater than the annual median, 0 otherwise;	Compustat
D_ITEM1_{it}	1 if firm i 's wildfire mentions are in the forward-looking statement, Item 1 or 1A of the 10-K filings, 0 otherwise;	SEC Edgar
$D_OTHER_ITEM_{it}$	1 if firm i 's wildfire mentions are in Items 2, 3, 6, 7, 7A, 8, 14, 15, the audit report, or the management internal control report of the 10-K filings, 0 otherwise;	SEC Edgar
$D_ITEM1\&7_{it}$	1 if firm i 's wildfire mentions are in the forward-looking statement, Item 1, Item 1A, Item 7, or Item 7A of the 10-K filings, 0 otherwise;	SEC Edgar
$D_OTHER_ITEM2_{it}$	1 if firm i 's wildfire mentions are in Items 2, 3, 6, 8, 14, 15, the audit report, or the management internal control report of the 10-K filings, 0 otherwise.	SEC Edgar
Control Variables		
BTM_{it}	Firm i 's book value of equity (ceq) divided by market capitalization ($csho \times prcc_f$) as of fiscal year t 's year end;	Compustat
LEV_{it}	Firm i 's total debt ($dltc + dltd$) divided by total assets (at) as of fiscal t 's year-end;	Compustat

<i>ROA_{it}</i>	Firm <i>i</i> 's earnings before interests and taxes (<i>ebit</i>) for fiscal year <i>t</i> divided by total assets (<i>at</i>) as of fiscal <i>t</i> 's year-end;	Compustat
<i>RET_{it}</i>	Firm <i>i</i> 's cumulative market-adjusted returns beginning nine months before fiscal year-end <i>t</i> to three months after fiscal year-end <i>t</i> ;	CRSP
<i>RET_VOL_{it}</i>	Firm <i>i</i> 's standard deviation of monthly stock returns beginning nine months before fiscal year-end <i>t</i> to three months after fiscal year-end <i>t</i> ;	CRSP
<i>LOG_G_SEG_{it}</i>	Natural logarithm of one plus <i>i</i> 's number of geographic segments (<i>goptp</i>) for fiscal year <i>t</i> ;	Compustat
<i>LOG_B_SEG_{it}</i>	Natural logarithm of one plus firm <i>i</i> 's number of business segments (<i>soptpi</i>) for fiscal year <i>t</i> ; and	Compustat
<i>LOG_TOTAL_WORDCNT_{it}</i>	Natural logarithm of one plus total word count in firm <i>i</i> 's 10-K filing for fiscal year <i>t</i> .	SEC Edgar

Compustat item mnemonics are shown in italics in parentheses.

Fig. 1 Regression Coefficients of Wildfire Disclosure for Treatment and Control Firms in the Pre-period and the Post-period

This figure plots the coefficients from the wildfire disclosure regression in Table 12 for both the treatment and the control firms in the pre and post-periods. We manually set the coefficient for the control group in the pre-period to zero since the intercept in the regression (-0.059) is contaminated by the inclusion of fixed effects and control variables. The coefficient for the control group in the post-period is -0.004 (0 plus the coefficient for *POST* -0.004). The coefficient for the treatment group in the pre-period is 0.11 (0 plus the coefficient for *TREAT* 0.11). The coefficient for the treatment group in the post-period is 0.028 (0.011 plus the coefficient for the interaction term *TREAT*POST* 0.017).

Fig. 2 Assumption of a Parallel Trend in the Pre-period

This figure plots the mean values of wildfire word count for years $t-2$, $t-1$, t , and $t+1$, respectively, where year t is the transition year. The transition year is defined as the year when a firm moves from a non-wildfire period ($WILDFIRE_DAYCNT = 0$) to a wildfire period ($WILDFIRE_DAYCNT > 0$). We see a clear parallel trend for the average wildfire word count from year $t-2$ to year $t-1$ in the pre-period and a much larger increase from year t to year $t+1$ in the post-period.

Table 1. Descriptive Statistics**Panel A: Total Observations**

Variables	N	25%	50%	Mean	75%	Std. Dev
<i>WILDFIRE_WORDCNT</i>	86,185	0	0	0.048	0	1.003
<i>LOG_WILDFIRE_WORDCNT</i>	86,185	0	0	0.018	0	0.152
<i>D_WILDFIRE_WORDCNT</i>	86,185	0	0	0.018	0	0.134
<i>WILDFIRE_DAYCNT</i>	86,185	0	0	0.986	0	4.090
<i>LOG_WILDFIRE_DAYCNT</i>	86,185	0	0	0.200	0	0.667
<i>D_WILDFIRE_DAYCNT</i>	86,185	0	0	0.100	0	0.301
<i>MCAP (in million)</i>	86,185	91	398	3,121	1,686	9,429
<i>LOG_MCAP</i>	86,185	4.516	5.990	6.037	7.431	2.043
<i>D_MCAP</i>	86,185	0	1	0.501	1	0.500
<i>WEST</i>	86,185	0	0	0.230	0	0.421
<i>UTILITY_BANKING</i>	86,185	0	0	0.120	0	0.325
<i>TANGIBLE_ASSET</i>	86,185	0.156	0.443	0.956	0.860	1.811
<i>D_TANGIBLE_ASSET</i>	86,185	0	1	0.570	1	0.495
<i>BTM</i>	86,185	0.270	0.500	0.625	0.824	0.594
<i>LEV</i>	86,185	0.030	0.180	0.232	0.366	0.225
<i>ROA</i>	86,185	-0.021	0.022	-0.036	0.064	0.237
<i>RET</i>	86,185	0.769	1.047	1.133	1.335	0.635
<i>RET_VOL</i>	86,185	0.072	0.110	0.135	0.171	0.092
<i>G_SEG</i>	86,185	2	3	5.168	6	5.349
<i>LOG_G_SEG</i>	86,185	1.099	1.386	1.533	1.946	0.722
<i>B_SEG</i>	86,185	2	3	4.980	8	4.488
<i>LOG_B_SEG</i>	86,185	1.099	1.386	1.546	2.197	0.680
<i>TOTAL_WORDCNT</i>	86,185	30,500	45,164	53,405	65,639	34,642
<i>LOG_TOTAL_WORDCNT</i>	86,185	10.326	10.718	10.707	11.092	0.599

Panel B: Partition by Wildfire Disclosers

Variables	Disclosers (<i>WILDFIRE_WORDCNT</i> >0)				Non-disclosers (<i>WILDFIRE_WORDCNT</i> =0)		Mean diff.		Median diff.	
	N	Mean	Median	N	Mean	Median	t-val	Sig.	z-val	Sig.
	(1)	(2)	(3)		(4)	(5)	(6)	(7)	(8)	
<i>WILDFIRE_WORDCNT</i>	1,587	2.622	1.000	84,598	0.000	0.000	0.000	15.10***	293.56***	
<i>LOG_WILDFIRE_WORDCNT</i>	1,587	0.981	0.693	84,598	0.000	0.000	0.000	69.68***	293.56***	
<i>WILDFIRE_DAYCNT</i>	1,587	3.873	0.000	84,598	0.932	0.000	0.000	14.65***	24.02***	
<i>LOG_WILDFIRE_DAYCNT</i>	1,587	0.665	0.000	84,598	0.191	0.000	0.000	16.02***	24.02***	
<i>D_WILDFIRE_DAYCNT</i>	1,587	0.273	0.000	84,598	0.097	0.000	0.000	15.64***	23.07***	
<i>MCAP</i>	1,587	5.095	1.356	84,598	3.084	389	7.45***	21.82***		
<i>LOG_MCAP</i>	1,587	7.111	7.213	84,598	6.017	5.966	23.49***	21.82***		
<i>D_MCAP</i>	1,587	0.661	1.000	84,598	0.497	0.000	13.61***	12.91***		
<i>WEST</i>	1,587	0.471	0.000	84,598	0.225	0.000	19.51***	23.10***		
<i>UTILITY_BANKING</i>	1,587	0.166	0.000	84,598	0.119	0.000	5.05***	5.79***		
<i>TANGIBLE_ASSET</i>	1,587	1.114	0.372	84,598	0.953	0.444	3.02***	-3.67***		
<i>D_TANGIBLE_ASSET</i>	1,587	0.643	1.000	84,598	0.569	1.000	6.07***	-5.88***		
<i>BTM</i>	1,587	0.638	0.598	84,598	0.625	0.498	0.97ns.	6.13***		
<i>LEV</i>	1,587	0.271	0.232	84,598	0.231	0.179	6.69***	8.06***		
<i>ROA</i>	1,587	-0.023	0.020	84,598	-0.036	0.022	2.54**	1.39ns.		
<i>RET</i>	1,587	1.124	1.097	84,598	1.133	1.046	-0.69ns.	2.78***		
<i>RET_VOL</i>	1,587	0.110	0.082	84,598	0.136	0.111	-12.05***	-15.91***		
<i>G_SEG</i>	1,587	3.885	3.000	84,598	5.192	3.000	-12.85***	-8.48***		
<i>LOG_G_SEG</i>	1,587	1.366	1.386	84,598	1.536	1.386	-10.86***	-8.48***		
<i>B_SEG</i>	1,587	5.771	3.000	84,598	4.965	3.000	6.31***	4.19***		
<i>LOG_B_SEG</i>	1,587	1.639	1.386	84,598	1.544	1.386	5.06***	4.19***		
<i>TOTAL_WORDCNT</i>	1,587	71,401	62,223	84,598	53,067	44,817	19.50***	25.21***		
<i>LOG_TOTAL_WORDCNT</i>	1,587	11.051	11.039	84,598	10.700	10.710	26.76***	25.21***		

This table presents the descriptive statistics for variables used in the regressions. Panel A presents the descriptive statistics for all observations. Panel B presents the descriptive statistics for wildfire disclosers and non-disclosers, respectively. See Appendix 3 for variable definitions.

Table 2. Descriptive Statistics by State, Industry, and Year

Panel A: By State

Rank	State	<i>WILDFIRE_</i> <i>DAYCNT</i>		<i>D_WILDFIRE_</i> <i>DAYCNT</i>		<i>WILDFIRE_</i> <i>WORDCNT</i>		<i>D_WILDFIRE_</i> <i>WORDCNT</i>		N_Total	N_Exposed to Wildfire	N_Disclosed Wildfire
		Mean	99%	Mean		Mean	99%	Mean				
1	HI	10.80	40	0.79		0.09		1		205	161	18
2	OR	5.90	61	0.20		0.02		0		791	157	6
3	CA	5.58	51	0.39		0.15		2		13,501	5,288	608
4	UT	3.91	99	0.21		0.01		0		678	144	7
5	ID	3.66	70	0.28		0.16		3		158	44	15
6	MT	2.47	31	0.09		0.00		0		75	7	-
7	WY	1.91	28	0.09		0.00		0		22	2	-
8	NV	1.63	33	0.20		0.15		1		755	153	24
9	WA	1.39	24	0.09		0.02		1		1,568	142	20
10	FL	0.91	18	0.21		0.04		1		3,784	783	66
All Other States		0.08	2	0.03		0.03		1		64,648	1,773	823

Panel B: By Industry

Rank	1-digit SIC	Industry	<i>WILDFIRE_</i> <i>DAYCNT</i>		<i>D_WILDFIRE_</i> <i>DAYCNT</i>		<i>WILDFIRE_</i> <i>WORDCNT</i>		<i>D_WILDFIRE_</i> <i>WORDCNT</i>		N_Total	N_Exposed to Wildfire	N_Disclosed Wildfire
			Mean	99%	Mean		Mean	99%	Mean				
1	0	Agriculture, Forestry & Fishing	2.88	36	0.22		0.06		1		249	54	9
2	2-3	Manufacturing	1.32	31	0.11		0.02		0		34,592	3,945	345
3	5	Wholesale & Retail Trade	1.09	27	0.10		0.02		1		8,281	835	110
4	7-8	Services	1.08	27	0.10		0.03		1		13,973	1,390	193
5	6	Finance, Insurance & Real Estate	1.06	27	0.09		0.07		2		17,850	1,561	573
6	4	Utilities & Transportation	0.81	24	0.08		0.19		2		6,786	562	143
7	1	Mining & Construction	0.61	16	0.07		0.09		2		4,297	297	211
8	9	Public Administration	0.57	8	0.06		0.05		1		157	10	3

Panel C: By Year

Year	<i>WILDFIRE_</i> <i>DAYCNT</i>		<i>D_WILDFIRE_</i> <i>DAYCNT</i>		<i>WILDFIRE_</i> <i>WORDCNT</i>		<i>D_WILDFIRE_</i> <i>WORDCNT</i>		N_Total	N_Exposed to Wildfire	N_Disclosed Wildfire
	Mean	99%	Mean		Mean	99%	Mean				
1996	0.36	7	0.08		0.00	0	0.00		4,390	343	12
1997	0.35	7	0.07		0.00	0	0.00		4,530	317	10
1998	0.41	7	0.10		0.01	0	0.00		4,411	432	9
1999	1.38	33	0.13		0.01	0	0.00		4,218	534	8
2000	0.94	22	0.12		0.01	0	0.00		4,200	516	9
2001	0.78	27	0.09		0.01	0	0.00		4,118	387	12
2002	2.64	51	0.13		0.01	0	0.00		3,860	505	15
2003	1.71	48	0.12		0.02	0	0.01		3,690	451	29
2004	0.89	14	0.08		0.02	0	0.01		3,847	325	30
2005	0.44	15	0.06		0.02	1	0.01		3,808	210	40
2006	0.69	15	0.07		0.02	0	0.01		3,733	273	35
2007	1.84	27	0.09		0.04	1	0.02		3,733	348	65
2008	1.19	24	0.10		0.05	1	0.02		3,772	362	69
2009	0.96	24	0.08		0.07	1	0.02		3,565	285	80
2010	0.46	15	0.08		0.06	1	0.02		3,446	280	79
2011	0.76	13	0.11		0.07	1	0.02		3,393	390	83
2012	0.82	24	0.10		0.07	1	0.03		3,352	329	88
2013	1.34	19	0.11		0.07	1	0.03		3,347	377	94
2014	1.08	20	0.11		0.07	1	0.03		3,421	361	106
2015	0.54	8	0.07		0.08	2	0.04		3,451	226	124
2016	2.36	55	0.11		0.10	2	0.04		3,412	364	136
2017	1.60	25	0.16		0.23	4	0.06		3,353	535	195
2018	3.27	35	0.16		0.18	3	0.08		3,135	504	259

This table presents the descriptive statistics of main variables *WILDFIRE_DAYCNT*, *D_WILDFIRE_DAYCNT*, *WILDFIRE_WORDCNT*, *D_WILDFIRE_WORDCNT* by state (Panel A), by industry (Panel B), and by year (Panel C). See Appendix 3 for variable definitions.

Table 3. Pearson Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1 <i>LOG_WILDFIRE_WORDCNT</i>	-															
2 <i>LOG_WILDFIRE_DAYCNT</i>	0.08	-														
3 <i>D_WILDFIRE_DAYCNT</i>	0.07	0.90	-													
4 <i>LOG_MCAP</i>	0.08	-0.05	-0.06	-												
5 <i>D_MCAP</i>	0.05	-0.04	-0.04	0.78	-											
6 <i>WEST</i>	0.07	0.43	0.39	-0.04	-0.03	-										
7 <i>UTILITY_BANKING</i>	0.03	-0.01	-0.01	0.04	-0.01	-0.06	-									
8 <i>TANGIBLE_ASSET</i>	0.02	-0.00	0.00	-0.02	-0.03	0.03	-0.05	-								
9 <i>D_TANGIBLE_ASSET</i>	0.02	-0.01	-0.01	0.03	0.01	-0.03	0.27	0.33	-							
10 <i>BTM</i>	0.01	-0.01	-0.01	-0.35	-0.27	-0.06	0.12	-0.01	0.09	-						
11 <i>LEV</i>	0.01	-0.02	-0.02	0.09	0.10	-0.09	-0.01	0.14	0.17	-0.08	-					
12 <i>ROA</i>	0.011	-0.07	-0.063	0.32	0.28	-0.12	0.07	-0.24	-0.12	0.05	-0.01	-				
13 <i>RET</i>	-0.00	0.00	-0.00	0.12	0.10	0.01	-0.02	-0.03	-0.03	-0.19	-0.04	0.15	-			
14 <i>RET_VOL</i>	-0.04	0.05	0.06	-0.39	-0.27	0.13	-0.21	0.11	-0.08	0.06	-0.02	-0.44	0.08	-		
15 <i>LOG_G_SEG</i>	-0.03	-0.00	-0.01	0.22	0.18	0.08	-0.33	-0.03	-0.13	-0.10	-0.04	0.11	0.03	0.01	-	
16 <i>LOG_B_SEG</i>	0.02	-0.01	-0.01	0.18	0.15	-0.06	-0.24	0.03	-0.09	-0.00	0.08	0.08	0.02	-0.04	0.32	-
17 <i>LOG_TOTAL_WORDCNT</i>	0.08	0.02	0.01	0.39	0.25	0.02	0.14	0.07	0.07	-0.06	0.21	-0.06	-0.02	-0.07	0.07	0.13

Panel B presents Pearson correlation coefficients for the key variables. The significant correlation coefficients at the 0.05 level are boldfaced. See Appendix 3 for variable definitions.

Table 4. Regression Analysis of Wildfire Word Count on Wildfire Firms

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	0.012***	(3.43)		
<i>D_WILDFIRE_DAYCNT</i>			0.021***	(3.18)
<i>LOG_MCAP</i>	0.004***	(4.15)	0.004***	(4.13)
<i>WEST</i>	0.052***	(3.96)	0.055***	(4.09)
<i>UTILITY_BANKING</i>	0.037***	(4.21)	0.037***	(4.21)
<i>TANGIBLE_ASSET</i>	0.002**	(2.35)	0.002**	(2.34)
<i>BTM</i>	0.003*	(1.87)	0.003*	(1.87)
<i>LEV</i>	0.003	(0.49)	0.002	(0.49)
<i>ROA</i>	-0.000	(-0.07)	-0.000	(-0.08)
<i>RET</i>	-0.001	(-0.98)	-0.001	(-0.95)
<i>RET_VOL</i>	0.014	(1.39)	0.014	(1.35)
<i>LOG_G_SEG</i>	-0.004	(-1.54)	-0.004	(-1.53)
<i>LOG_B_SEG</i>	0.004	(1.36)	0.004	(1.37)
<i>LOG_TOTAL_WORDCNT</i>	0.005***	(2.61)	0.005***	(2.63)
<i>constant</i>	-0.139***	(-4.47)	-0.139***	(-4.48)
N	86,185		86,185	
Adj. R ²	0.079		0.079	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 LOG_MCAP + \beta_3 WEST + \beta_4 \\
 & UTILITY_BANKING + \beta_5 TANGIBLE_ASSET + \beta_6 BTM + \beta_7 LEV + \beta_8 ROA + \beta_9 RET + \beta_{10} RET_VOL + \beta_{11} \\
 & LOG_G_SEG + \beta_{12} LOG_B_SEG + \beta_{13} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY \\
 & FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}
 \end{aligned}
 \tag{1}$$

Col. 1 uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. 2 uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Regression coefficients and *t*-stats. (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 5. Regression Analysis of Wildfire Word Count on Wildfire Firms over Time

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>		(1)	(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	-0.006***	(-4.72)		
<i>D_WILDFIRE_DAYCNT</i>			-0.013***	(-4.68)
<i>YR03_08</i>	0.004**	(2.54)	0.004**	(2.40)
<i>YR09_18</i>	0.021***	(8.19)	0.021***	(8.21)
<i>LOG_WILDFIRE_DAYCNT*FY03_08</i>	0.012***	(3.65)		
<i>LOG_WILDFIRE_DAYCNT*FY09_18</i>	0.037***	(5.13)		
<i>D_WILDFIRE_DAYCNT*FY03_08</i>			0.028***	(3.57)
<i>D_WILDFIRE_DAYCNT*FY09_18</i>			0.070***	(4.86)
<i>LOG_MCAP</i>	0.005***	(4.82)	0.005***	(4.83)
<i>WEST</i>	0.053***	(3.99)	0.055***	(4.14)
<i>UTILITY_BANKING</i>	0.032***	(3.88)	0.032***	(3.89)
<i>TANGIBLE_ASSET</i>	0.002**	(2.37)	0.002**	(2.36)
<i>BTM</i>	0.003**	(2.10)	0.003**	(2.15)
<i>LEV</i>	0.005	(1.04)	0.006	(1.12)
<i>ROA</i>	-0.000	(-0.06)	-0.000	(-0.08)
<i>RET</i>	-0.003***	(-4.23)	-0.003***	(-4.24)
<i>RET_VOL</i>	0.021**	(2.11)	0.020**	(2.05)
<i>LOG_G_SEG</i>	-0.006**	(-2.00)	-0.006**	(-2.05)
<i>LOG_B_SEG</i>	0.002	(0.62)	0.001	(0.56)
<i>LOG_TOTAL_WORDCNT</i>	0.005**	(2.57)	0.005**	(2.57)
<i>constant</i>	-0.133***	(-4.32)	-0.133***	(-4.32)
N	86,185		86,185	
Adj. R ²	0.080		0.078	
Year FE	No		No	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, year indicators, and an interaction between wildfire events and year indicators. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_{2,1} FY03_08 + \beta_{2,2} FY09_18 + \beta_{3,1} \\
 & WILDFIRE_EVENT*YR03_08 + \beta_{3,3} WILDFIRE_EVENT*YR09_18 + \beta_4 LOG_MCAP + \beta_5 WEST + \beta_6 \\
 & UTILITY_BANKING + \beta_7 TANGIBLE_ASSET + \beta_8 BTM + \beta_9 LEV + \beta_{10} ROA + \beta_{11} RET + \beta_{12} RET_VOL + \beta_{13} \\
 & LOG_G_SEG + \beta_{14} LOG_G_SEG + \beta_{15} LOG_TOTAL_WORDCNT + INDUSTRY\ FIXED\ EFFECTS + STATE \\
 & FIXED\ EFFECTS + \varepsilon_{it}
 \end{aligned}
 \tag{2a}$$

Col. 1 uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. 2 uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. *YR03_08* and *YR_09_18* equal to one for observations in fiscal years 2003-2008 and 2009-2018, respectively, zero otherwise. Regression coefficients and *t*-stats. (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 6. Regression Analysis of Wildfire Word Count on High Market Capitalization Firms

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>		(1)	(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	0.003	(1.56)		
<i>D_WILDFIRE_DAYCNT</i>			0.005	(1.23)
<i>D_MCAP</i>	0.007***	(2.74)	0.007***	(2.88)
<i>LOG_WILDFIRE_DAYCNT*D_MCAP</i>	0.020**	(2.50)		
<i>D_WILDFIRE_DAYCNT*D_MCAP</i>			0.036**	(2.31)
<i>WEST</i>	0.053***	(4.00)	0.056***	(4.13)
<i>UTILITY_BANKING</i>	0.038***	(4.04)	0.038***	(4.01)
<i>TANGIBLE_ASSET</i>	-0.003	(-1.13)	-0.003	(-1.13)
<i>BTM</i>	0.003**	(2.45)	0.003**	(2.43)
<i>LEV</i>	0.001	(0.43)	0.001	(0.49)
<i>ROA</i>	0.001	(0.19)	0.001	(0.18)
<i>RET</i>	0.002	(0.83)	0.002	(0.84)
<i>RET_VOL</i>	-0.000	(-0.55)	-0.000	(-0.54)
<i>LOG_G_SEG</i>	0.002	(0.23)	0.002	(0.24)
<i>LOG_B_SEG</i>	0.004	(1.59)	0.004	(1.58)
<i>LOG_TOTAL_WORDCNT</i>	0.007***	(3.12)	0.007***	(3.11)
<i>constant</i>	-0.143***	(-4.34)	-0.143***	(-4.34)
N	86,185		86,185	
Adj. R ²	0.081		0.079	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, an indicator for firms with higher than annual median market capitalization (*D_MCAP*), and an interaction between wildfire events and *D_MCAP*. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 D_MCAP + \beta_3 WILDFIRE_EVENT*D_MCAP \\
 & + \beta_4 WEST + \beta_5 UTILITY_BANKING + \beta_6 TANGIBLE_ASSET + \beta_7 BTM + \beta_8 LEV + \beta_9 ROA + \beta_{10} RET + \beta_{11} \\
 & RET_VOL + \beta_{12} LOG_G_SEG + \beta_{13} LOG_G_SEG + \beta_{14} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + \\
 & INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}.
 \end{aligned}
 \tag{2b}$$

Col. 1 uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. 2 uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. *D_MCAP* equals to one for firms with higher than annual median market capitalization, zero otherwise. Regression coefficients and *t*-stats. (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 7. Regression Analysis of Wildfire Word Count on Firms in the West Region

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>		(1)	(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	-0.000	(-0.08)		
<i>D_WILDFIRE_DAYCNT</i>			0.001	(0.15)
<i>WEST</i>	0.051***	(3.86)	0.051***	(3.85)
<i>LOG_WILDFIRE_DAYCNT*WEST</i>	0.014***	(2.98)		
<i>D_WILDFIRE_DAYCNT*WEST</i>			0.031***	(2.88)
<i>LOG_MCAP</i>	0.004***	(4.16)	0.004***	(4.16)
<i>UTILITY_BANKING</i>	0.037***	(4.21)	0.038***	(4.21)
<i>TANGIBLE_ASSET</i>	0.002**	(2.36)	0.002**	(2.36)
<i>BTM</i>	0.003*	(1.89)	0.003*	(1.92)
<i>LEV</i>	0.003	(0.52)	0.003	(0.51)
<i>ROA</i>	-0.000	(-0.05)	-0.000	(-0.07)
<i>RET</i>	-0.001	(-1.01)	-0.001	(-1.00)
<i>RET_VOL</i>	0.014	(1.41)	0.014	(1.39)
<i>LOG_G_SEG</i>	-0.004	(-1.55)	-0.004	(-1.56)
<i>LOG_B_SEG</i>	0.004	(1.36)	0.004	(1.34)
<i>LOG_TOTAL_WORDCNT</i>	0.005***	(2.60)	0.005***	(2.61)
<i>constant</i>	-0.138***	(-4.47)	-0.139***	(-4.48)
N	86,185		86,185	
Adj. R ²	0.080		0.079	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, an indicator for firms in the western states (*WEST*), and an interaction between wildfire events and *WEST*. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 WEST + \beta_3 WILDFIRE_EVENT*WEST + \beta_4 \\
 & LOG_MCAP + \beta_5 UTILITY_BANKING + \beta_6 TANGIBLE_ASSET + \beta_7 BTM + \beta_8 LEV + \beta_9 ROA + \beta_{10} RET + \beta_{11} \\
 & RET_VOL + \beta_{12} LOG_G_SEG + \beta_{13} LOG_G_SEG + \beta_{14} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + \\
 & INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}.
 \end{aligned}
 \tag{2c}$$

Col. 1 uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. 2 uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. *WEST* equals to one for firms in the western states (i.e., AK, CA, CO, HI, ID, MT, NV, OR, UT, WA, WY), zero otherwise. Regression coefficients and *t*-stats. (in parentheses) are reported. State fixed effects exclude western states but include other states. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 8. Regression Analysis of Wildfire Word Count on Utility and Banking Firms

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	0.005**	(2.40)		
<i>D_WILDFIRE_DAYCNT</i>			0.008**	(1.97)
<i>UTILITY_BANKING</i>	0.027***	(3.91)	0.027***	(3.97)
<i>LOG_WILDFIRE_DAYCNT*UTILITY_BANKING</i>	0.063**	(2.35)		
<i>D_WILDFIRE_DAYCNT*UTILITY_BANKING</i>			0.116**	(2.16)
<i>LOG_MCAP</i>	0.004***	(4.21)	0.004***	(4.18)
<i>WEST</i>	0.050***	(3.81)	0.053***	(3.99)
<i>TANGIBLE_ASSET</i>	0.002**	(2.35)	0.002**	(2.34)
<i>BTM</i>	0.002*	(1.73)	0.002*	(1.72)
<i>LEV</i>	0.002	(0.30)	0.001	(0.27)
<i>ROA</i>	-0.001	(-0.41)	-0.001	(-0.36)
<i>RET</i>	-0.001	(-0.76)	-0.001	(-0.89)
<i>RET_VOL</i>	0.012	(1.12)	0.012	(1.14)
<i>LOG_G_SEG</i>	-0.004*	(-1.67)	-0.004*	(-1.65)
<i>LOG_B_SEG</i>	0.004	(1.36)	0.003	(1.29)
<i>LOG_TOTAL_WORDCNT</i>	0.005***	(2.62)	0.005***	(2.65)
<i>constant</i>	-0.135***	(-4.48)	-0.136***	(-4.49)
N	86,185		86,185	
Adj. R ²	0.087		0.084	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, an indicator for firms in the utility and banking industries (*UTILITY_BANKING*), and an interaction between wildfire events and *UTILITY_BANKING*. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 UTILITY_BANKING + \beta_3 \\
 & WILDFIRE_EVENT*UTILITY_BANKING + \beta_4 LOG_MCAP + \beta_5 WEST + \beta_6 TANGIBLE_ASSET + \beta_7 BTM + \beta_8 \\
 & LEV + \beta_9 ROA + \beta_{10} RET + \beta_{11} RET_VOL + \beta_{12} LOG_G_SEG + \beta_{13} LOG_B_SEG + \beta_{14} LOG_TOTAL_WORDCNT \\
 & + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}
 \end{aligned}
 \tag{2d}$$

Col. (1) uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. (2) uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. *UTILITY_BANKING* equals to one for firms in the utility and banking industries (SIC 4900 to 4999, 6000 to 6299 following Fama French 48 industry classifications), zero otherwise. Regression coefficients and *t*-stats. (in parentheses) are reported. Industry fixed effects are based on the 4-digit SIC code and exclude utility and banking. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 9. Regression Analysis of Wildfire Word Count and Firms with High Tangible Assets

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	0.001	(0.57)		
<i>D_WILDFIRE_DAYCNT</i>			-0.000	(-0.05)
<i>D_TANGIBLE_ASSET</i>	-0.000	(-0.05)	-0.000	(-0.07)
<i>LOG_WILDFIRE_DAYCNT*D_TANGIBLE_ASSET</i>	0.019***	(2.81)		
<i>D_WILDFIRE_DAYCNT*D_TANGIBLE_ASSET</i>			0.038***	(2.90)
<i>LOG_MCAP</i>	0.004***	(4.10)	0.004***	(4.07)
<i>WEST</i>	0.053***	(3.98)	0.055***	(4.12)
<i>UTILITY_BANKING</i>	0.037***	(4.17)	0.037***	(4.16)
<i>BTM</i>	0.003*	(1.85)	0.003*	(1.86)
<i>LEV</i>	0.004	(0.82)	0.004	(0.79)
<i>ROA</i>	-0.002	(-0.71)	-0.002	(-0.72)
<i>RET</i>	-0.001	(-0.94)	-0.001	(-0.91)
<i>RET_VOL</i>	0.015	(1.46)	0.015	(1.43)
<i>LOG_G_SEG</i>	-0.004	(-1.57)	-0.004	(-1.57)
<i>LOG_B_SEG</i>	0.004	(1.52)	0.004	(1.53)
<i>LOG_TOTAL_WORDCNT</i>	0.005***	(2.64)	0.005***	(2.67)
<i>constant</i>	-0.139***	(-4.50)	-0.140***	(-4.51)
N	86,185		86,185	
Adj. R ²	0.081		0.080	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, an indicator for firms with higher than annual median tangible assets (*D_TANGIBLE_ASSET*), and an interaction between wildfire events and *D_TANGIBLE_ASSET*. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 D_TANGIBLE_ASSET + \beta_3 \\
 & WILDFIRE_EVENT * D_TANGIBLE_ASSET + \beta_4 LOG_MCAP + \beta_5 WEST + \beta_6 UTILITY_BANKING + \beta_7 BTM + \\
 & \beta_8 LEV + \beta_9 ROA + \beta_{10} RET + \beta_{11} RET_VOL + \beta_{12} LOG_G_SEG + \beta_{13} LOG_B_SEG + \beta_{14} \\
 & LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED \\
 & EFFECTS + \varepsilon_{it}
 \end{aligned}
 \tag{2e}$$

Col. (1) uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. (2) uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. *D_TANGIBLE_ASSET* equals to one for firms with higher than annual median tangible assets, zero otherwise. Regression coefficients and *t*-stats. (in parentheses) are reported. State fixed effects are excluded since firms with more than one segment (i.e., multinational firms) tend to be clustered in a few states. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 10. Disclosure Location of Wildfire Keyword in 10-K Filings

Panel A: The Number of Location Mentions by Item Numbers					
	<i>N</i>	<i>D_ITEM1</i>	<i>D_OTHER_ITEM</i>	<i>D_ITEM1&7</i>	<i>D_OTHER_ITEM2</i>
	(1)	(2)	(3)	(4)	(5)
Forward-Looking Statement	53	35	0	46	0
ITEM 1: Business	280	163	0	194	0
ITEM 1A: Risk Factors	1,121	945	0	1,030	0
ITEM 2: Properties	2	0	2	0	2
ITEM 3: Legal Proceedings	15	0	15	0	15
ITEM 6: Selected Financial Data	17	0	17	0	17
ITEM 7: MD&A	337	0	337	224	0
ITEM 7A: Quantitative & Qualitative Disclosures About Market Risk	17	0	17	15	0
ITEM 8: Financial Statements and Supplementary Data	156	0	156	0	156
ITEM 14: Principal Accounting Fees and Services	4	0	4	0	4
ITEM 15: Exhibits and Financial Statement Schedules	107	0	107	0	107
Report of Independent Registered Public Accounting Firm	3	0	3	0	3
Management's Report on Internal Control over Financial Reporting	1	0	1	0	1
Total mentions	2,113	1,143	659	1,463	305

Panel B: The Number of Location Mentions by the Number of Disclosure Location		
# of Location Count	<i>N</i>	Percent
0	84,598	98.16
1	1,268	1.47
2	192	0.22
3	69	0.08
4	44	0.05
5	10	0.01
6	1	0.00
7	2	0.00
8	1	0.00
Total mentions	2,113	
Total firm-years	1,587	

This table presents the disclosure location of wildfire keyword mentions in 10-K filings. Panel A presents the number of location mentions by item numbers. Col. *N* indicates the number of location mentions in each item. For example, the 1,121 for item 1A risk factors indicates that 1,121 firm-years in our sample mention wildfire in item 1A at least once. Col. *D_ITEM1* indicates the number of location mentions in the forward-looking statement, item 1 or item 1A only. Col. *D_ITEM_OTHER* indicates the number of location mentions in items 2, 3, 6, 7, 7A, 8, 14, 15, audit report, or the management internal control report. *D_ITEM1&7* indicates the number of location mentions in the forward-looking statement, item 1, item 1A, item 7 or item 7A only. *D_ITEM_OTHER2* indicates the number of location mentions for items 2, 3, 6, 8, 14, 15, audit report, or the management internal control report. Panel B presents the number of location mentions by the number of disclosure location. 84,598 firm-year observations have no mentions of wildfire, 1,268 firm-year observations mention wildfire in one item; 192 firm-year observations mention wildfire in two items, and 69 firm-year observations mentioned wildfire in three items, and so on.

Table 11. Regression of Wildfire Word Count on Firms that Likely Have Had Wildfires Affecting Their Past operations

Panel A: Regression on <i>D_ITEM1</i> and <i>D_OTHER_ITEM</i>				
Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>				
	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	-0.000	(-1.28)		
<i>D_WILDFIRE_DAYCNT</i>			-0.001	(-1.12)
<i>D_ITEM1</i>	0.793***	(52.72)	0.791***	(52.43)
<i>D_OTHER_ITEM</i>	1.326***	(20.42)	1.308***	(20.37)
<i>LOG_WILDFIRE_DAYCNT*D_ITEM1</i>	0.000	(0.01)		
<i>LOG_WILDFIRE_DAYCNT*D_OTHER_ITEM</i>	0.191**	(2.06)		
<i>D_WILDFIRE_DAYCNT*D_ITEM1</i>			0.006	(0.24)
<i>D_WILDFIRE_DAYCNT*D_OTHER_ITEM</i>			0.560**	(2.14)
<i>LOG_MCAP</i>	0.000	(1.34)	0.000	(1.39)
<i>WEST</i>	0.006***	(2.78)	0.006***	(2.74)
<i>UTILITY_BANKING</i>	0.004	(1.35)	0.004	(1.37)
<i>TANGIBLE_ASSET</i>	0.001*	(1.87)	0.001*	(1.86)
<i>BTM</i>	0.001	(1.28)	0.001	(1.26)
<i>LEV</i>	-0.002	(-1.36)	-0.002	(-1.37)
<i>ROA</i>	0.001	(0.68)	0.001	(0.51)
<i>RET</i>	-0.000	(-0.11)	-0.000	(-0.06)
<i>RET_VOL</i>	-0.001	(-0.17)	-0.001	(-0.15)
<i>LOG_G_SEG</i>	-0.000	(-0.17)	-0.000	(-0.24)
<i>LOG_B_SEG</i>	-0.000	(-0.40)	-0.000	(-0.36)
<i>LOG_TOTAL_WORDCNT</i>	0.002**	(2.38)	0.002**	(2.37)
<i>constant</i>	-0.026***	(-2.76)	-0.025***	(-2.75)
N	86,185		86,185	
Adj. R ²	0.823		0.825	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

Panel B: Regression on *D_ITEM1&7* and *D_OTHER_ITEM2*

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	-0.000	(-0.65)		
<i>D_WILDFIRE_DAYCNT</i>			-0.000	(-0.60)
<i>D_ITEM1&7</i>	0.855***	(46.70)	0.855***	(46.22)
<i>D_OTHER_ITEM2</i>	1.533***	(15.20)	1.507***	(14.98)
<i>LOG_WILDFIRE_DAYCNT*D_ITEM1&7</i>	-0.011	(-1.06)		
<i>LOG_WILDFIRE_DAYCNT*D_OTHER_ITEM2</i>	0.267***	(2.69)		
<i>D_WILDFIRE_DAYCNT*D_ITEM1&7</i>			-0.027	(-0.96)
<i>D_WILDFIRE_DAYCNT*D_OTHER_ITEM2</i>			0.748**	(2.56)
<i>LOG_MCAP</i>	0.000	(0.53)	0.000	(0.64)
<i>WEST</i>	0.004	(1.56)	0.004	(1.59)
<i>UTILITY_BANKING</i>	0.004	(1.50)	0.004	(1.56)
<i>TANGIBLE_ASSET</i>	0.001**	(2.03)	0.001**	(2.02)
<i>BTM</i>	0.000	(0.47)	0.000	(0.46)
<i>LEV</i>	-0.003	(-1.62)	-0.003	(-1.59)
<i>ROA</i>	0.002	(1.63)	0.001	(1.41)
<i>RET</i>	-0.000	(-0.48)	-0.000	(-0.41)
<i>RET_VOL</i>	-0.001	(-0.30)	-0.001	(-0.35)
<i>LOG_G_SEG</i>	-0.000	(-0.18)	-0.000	(-0.21)
<i>LOG_B_SEG</i>	0.000	(0.37)	0.000	(0.41)
<i>LOG_TOTAL_WORDCNT</i>	0.001**	(2.22)	0.001**	(2.18)
<i>constant</i>	-0.021**	(-2.49)	-0.020**	(-2.47)
N	86,185		86,185	
Adj. R ²	0.833		0.835	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on county-level wildfire events, an indicator for the wildfire disclosure location, and an interaction between wildfire events and the disclosure location. For the disclosure location variables, Panel A presents the results for an indicator for firms mentioning wildfire in the forward-looking statement, item 1 or item 1A only (*D_ITEM1*), and an indicator for firms mentioning wildfire in items 2, 3, 6, 7, 7A, 8, 14, 15, audit report, or the management internal control report (*D_OTHER_ITEM*); Panel B presents the results for an indicator for firms mentioning wildfire in the forward-looking statement, item 1, item 1A, item 7, or item 7A only (*D_ITEM1&7*), and an indicator for firms mentioning wildfire in items 2, 3, 6, 8, 14, 15, audit report, or the management internal control report (*D_OTHER_ITEM2*). The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_{2,1} D_ITEM1 + \beta_{2,2} D_OTHER_ITEM + \beta_{3,1} \\
 & WILDFIRE_EVENT * D_ITEM1 + \beta_{3,1} WILDFIRE_EVENT * D_OTHER_ITEM + \beta_4 LOG_MCAP + \beta_5 WEST \\
 & + \beta_6 UTILITY_BANKING + \beta_7 TANGIBLE_ASSET + \beta_8 BTM + \beta_9 LEV + \beta_{10} ROA + \beta_{11} RET + \beta_{12} RET_VOL + \\
 & \beta_{13} LOG_G_SEG + \beta_{14} LOG_B_SEG + \beta_{15} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY \\
 & FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}.
 \end{aligned}
 \tag{2f}$$

Col. (1) uses the natural logarithm of the total number of days in a year with a wildfire in a headquarter county (*LOG_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Col. (2) uses an indicator variable of wildfire occurrence in a headquarter county in a year (*D_WILDFIRE_DAYCNT*) to measure the level of wildfire events. Regression coefficients and *t*-stats. (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 12. Difference-in-Differences Analysis of Wildfire Disclosure

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>		
	Coeff.	t-stat.
<i>TREAT</i>	0.011	(1.51)
<i>POST</i>	-0.004	(-0.77)
<i>TREAT*POST</i>	0.017**	(2.26)
<i>LOG_MCAP</i>	0.011***	(3.10)
<i>WEST</i>	0.071**	(2.52)
<i>UTILITY_BANKING</i>	0.109	(1.51)
<i>TANGIBLE_ASSET</i>	0.000	(0.20)
<i>BTM</i>	0.014**	(2.44)
<i>LEV</i>	0.009	(0.77)
<i>ROA</i>	-0.002	(-0.24)
<i>RET</i>	0.001	(0.23)
<i>RET_VOL</i>	0.044	(1.47)
<i>LOG_G_SEG</i>	-0.009*	(-1.72)
<i>LOG_B_SEG</i>	0.009	(1.07)
<i>LOG_TOTAL_WORDCNT</i>	-0.006	(-1.13)
<i>constant</i>	-0.059	(-1.01)
N	3,720	
Adj. R ²	0.103	
Year FE	Yes	
Industry FE	Yes	
State FE	Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on treatment firms and controls in the pre- and post-periods. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 TREAT + \beta_2 POST + \beta_3 TREAT*POST + \beta_4 WEST + \beta_5 UTILITY_ \\
 & BANKING + \beta_6 TANGIBLE_ASSET + \beta_7 BTM + \beta_8 LEV + \beta_9 ROA + \beta_{10} RET + \beta_{11} RET_VOL + \beta_{12} LOG_G_SEG + \\
 & \beta_{13} LOG_B_SEG + \beta_{14} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED\ EFFECTS + \\
 & STATE\ FIXED\ EFFECTS + \varepsilon_{it}.
 \end{aligned}
 \tag{3}$$

TREAT equals 1 for wildfire-affected firms, and 0 for control firms. Control firms are not exposed to wildfires in their headquarter counties but of similar market capitalization and in the same industry (SIC 2 digit) and year as the wildfire exposure firms from year $t-1$ to $t+1$. *POST* equals 1 for the post-wildfire period, and 0 for the pre-wildfire period. The transition year t is excluded in the analysis. The transition year is defined as the year when a firm moves from a non-wildfire period (*WILDFIRE_DAYCNT*=0) to a wildfire period (*WILDFIRE_DAYCNT*>0). Regression coefficients and t -stats. (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variable represents the main variable of interest.

Table 13. Regression Analysis of Wildfire Word Count on Weighted Average Wildfire Day Count of a Firm's Operations across Multiple States

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WEIGHTED_DAYCNT</i>	0.004***	(4.32)		
<i>D_WEIGHTED_DAYCNT</i>			0.007***	(3.94)
<i>LOG_MCAP</i>	0.004***	(3.74)	0.004***	(3.80)
<i>WEST</i>	0.053***	(4.03)	0.055***	(4.19)
<i>UTILITY_BANKING</i>	0.041***	(4.41)	0.039***	(4.29)
<i>TANGIBLE_ASSET</i>	0.002**	(2.36)	0.002**	(2.34)
<i>BTM</i>	0.002	(1.60)	0.002	(1.61)
<i>LEV</i>	0.003	(0.53)	0.003	(0.51)
<i>ROA</i>	-0.001	(-0.28)	-0.001	(-0.29)
<i>RET</i>	-0.001	(-1.05)	-0.001	(-1.03)
<i>RET_VOL</i>	0.014	(1.29)	0.014	(1.35)
<i>LOG_G_SEG</i>	-0.004*	(-1.66)	-0.004*	(-1.66)
<i>LOG_B_SEG</i>	0.004	(1.46)	0.004	(1.46)
<i>LOG_TOTAL_WORDCNT</i>	0.005**	(2.36)	0.005**	(2.53)
<i>constant</i>	-0.137***	(-4.32)	-0.137***	(-4.32)
N	81,704		81,704	
Adj. R ²	0.080		0.080	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on the weighted average wildfire day count of a firm's operations across multiple states. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WEIGHTED_WILDFIRE_EVENT + \beta_2 LOG_MCAP + \beta_3 WEST + \beta_4 \\
 & UTILITY_BANKING + \beta_5 TANGIBLE_ASSET + \beta_6 BTM + \beta_7 LEV + \beta_8 ROA + \beta_9 RET + \beta_{10} RET_VOL + \beta_{11} \\
 & LOG_G_SEG + \beta_{12} LOG_B_SEG + \beta_{13} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED \\
 & EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}
 \end{aligned}
 \tag{4}$$

The weighted average measure is calculated using the number of wildfire days in all mentioned states in items 1, 2, 6, and 7 of the 10-Ks weighted by the number of mentions. Regression coefficients and t-values (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 14. Regression Analysis of Wildfire Word Count on the Interaction between Wildfire Events and Headquarter Concentration

Dependent Variable: <i>LOG_WILDFIRE_WORDCNT</i>	(1)		(2)	
	Coeff.	t-stat.	Coeff.	t-stat.
<i>LOG_WILDFIRE_DAYCNT</i>	0.005**	(2.16)		
<i>D_WILDFIRE_DAYCNT</i>			0.008*	(1.73)
<i>HIGH_CONCEN</i>	0.001	(0.45)	0.001	(0.42)
<i>LOG_WILDFIRE_DAYCNT* HIGH_CONCEN</i>	0.015**	(1.96)		
<i>D_WILDFIRE_DAYCNT* HIGH_CONCEN</i>			0.031**	(2.04)
<i>LOG_MCAP</i>	0.004***	(4.13)	0.004***	(4.11)
<i>WEST</i>	0.050***	(3.92)	0.052***	(4.04)
<i>UTILITY_BANKING</i>	0.036***	(3.87)	0.036***	(3.87)
<i>TANGIBLE_ASSET</i>	0.002**	(2.36)	0.002**	(2.35)
<i>BTM</i>	0.003*	(1.76)	0.003*	(1.78)
<i>LEV</i>	0.003	(0.65)	0.003	(0.65)
<i>ROA</i>	-0.002	(-0.56)	-0.002	(-0.57)
<i>RET</i>	-0.001	(-1.20)	-0.001	(-1.16)
<i>RET_VOL</i>	0.017	(1.56)	0.016	(1.50)
<i>LOG_G_SEG</i>	-0.004*	(-1.68)	-0.004*	(-1.68)
<i>LOG_B_SEG</i>	0.004	(1.48)	0.004	(1.47)
<i>LOG_TOTAL_WORDCNT</i>	0.005***	(2.67)	0.005***	(2.69)
<i>constant</i>	-0.141***	(-4.46)	-0.142***	(-4.47)
N	81,704		81,704	
Adj. R ²	0.082		0.082	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on the interaction between wildfire events and headquarter concentration. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT + \beta_2 HIGH_CONCEN + \beta_3 \\
 & WILDFIRE_EVENT*HIGH_CONCEN + \beta_4 LOG_MCAP + \beta_5 WEST + \beta_6 TANGIBLE_ASSET + \beta_7 BTM + \beta_8 LEV + \beta_9 \\
 & ROA + \beta_{10} RET + \beta_{11} RET_VOL + \beta_{12} LOG_G_SEG + \beta_{13} LOG_B_SEG + \beta_{14} LOG_TOTAL_WORDCNT + YEAR \\
 & FIXED\ EFFECTS + INDUSTRY\ FIXED\ EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}.
 \end{aligned} \tag{5}$$

High headquarter concentration (*HIGH_CONCEN*) is an indicator that equals 1 when the ratio of the number of mentions of the headquarter state relative to all states mentioned in items 1, 2, 6 and 7 of 10-Ks is greater than 50%, and 0 otherwise. Regression coefficients and t-values (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.

Table 15. Event Analysis for Insurance Companies around the Wildfire Events

Panel A: Country level							
	N	Fama-French 4- factor CAR	t-stat.	Signif.	Value-weighted CAR	t-stat.	Signif.
<i>CAR0</i>	657,486	0.00012	2.284	***	0.00155	28.885	***
<i>CAR7</i>	760,421	-0.00023	-2.743	***	0.00349	42.508	***
<i>CAR30</i>	760,421	0.00049	3.209	***	0.01041	71.249	***
Panel B: Region level							
	N	Fama-French 4- factor CAR	t-stat.	p-val.	Value-weighted CAR	t-stat.	p-val.
<i>CAR0</i>	86,461	0.00035	2.147	**	0.00176	10.774	***
<i>CAR7</i>	102,109	0.00066	2.664	***	0.00464	18.985	***
<i>CAR30</i>	102,109	0.00383	8.273	***	0.01463	33.850	***
Panel C: State level							
	N	Fama-French 4- factor CAR	t-stat.	p-val.	Value-weighted CAR	t-stat.	p-val.
<i>CAR0</i>	24,235	-0.00059	-1.900	**	0.00043	1.393	ns
<i>CAR7</i>	28,896	-0.00089	-1.788	**	0.00207	4.313	***
<i>CAR30</i>	28,896	0.00116	1.199	ns	0.01073	12.153	***

This table presents the Fama-French cumulative abnormal returns (CAR) and value-weighted market-adjusted CAR for insurance companies during the wildfire episode periods. An episode contains multiple wildfire events that occur during same time period and at nearby counties/zones. Three windows are examined: *CAR0* (the episode period), *CAR7* (the episode period plus seven trading days after the episode period), and *CAR30* (the episode period plus thirty trading days after the episode period). Panel A presents the results at the country level, assuming that wildfire firms likely purchase insurance coverage from insurance companies all over the country, and thus all insurance companies' stock returns could be affected when wildfires happen. Panels B and C present the results at the region and state levels, assuming that wildfire firms likely purchase insurance coverage from insurance companies in the same region/state, and thus the stock returns of insurance companies in the same region/state should be negatively affected when wildfires happen. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests.

Table 16. Regression Analysis of Wildfire Word Count on the Wildfire Events of Firms in the Same County of the Events versus Firms in Neighboring Counties

Dependent Variable: <i>LOG_WILDFIRE_DAYCNT</i>	(1)		(2)	
	coeff.	<i>t</i> -stat.	coeff.	<i>t</i> -stat.
<i>LOG_WILDFIRE_DAYCNT_SAME</i>	0.009***	(3.91)		
<i>LOG_WILDFIRE_DAYCNT_NEIGHBOR</i>	0.004**	(2.53)		
<i>D_WILDFIRE_DAYCNT_SAME</i>			0.024***	(3.45)
<i>D_WILDFIRE_DAYCNT_NEIGHBOR</i>			0.006**	(2.23)
<i>LOG_MCAP</i>	0.004***	(4.16)	0.004***	(4.13)
<i>WEST</i>	0.051***	(3.86)	0.053***	(3.97)
<i>UTILITY_BANKING</i>	0.039***	(4.33)	0.038***	(4.26)
<i>TANGIBLE_ASSET</i>	0.002**	(2.37)	0.002**	(2.36)
<i>BTM</i>	0.003*	(1.89)	0.003*	(1.88)
<i>LEV</i>	0.002	(0.45)	0.002	(0.46)
<i>ROA</i>	-0.000	(-0.11)	-0.000	(-0.10)
<i>RET</i>	-0.001	(-1.02)	-0.001	(-0.97)
<i>RET_VOL</i>	0.014	(1.37)	0.014	(1.34)
<i>LOG_G_SEG</i>	-0.004	(-1.51)	-0.004	(-1.51)
<i>LOG_B_SEG</i>	0.004	(1.35)	0.004	(1.34)
<i>LOG_TOTAL_WORDCNT</i>	0.005**	(2.56)	0.005***	(2.59)
<i>constant</i>	-0.138***	(-4.45)	-0.138***	(-4.45)
F-test of <i>WILDFIRE_DAYCNT_SAME=WILDFIRE_DAYCNT_NEIGHBOR</i>				
	F-stat = 6.28		F-stat = 7.75	
	P-value = 0.012		P-value = 0.005	
N	86,185		86,185	
Adj. R ²	0.079		0.078	
Year FE	Yes		Yes	
Industry FE	Yes		Yes	
State FE	Yes		Yes	

This table presents the results of regressing the natural logarithm of wildfire word count in 10-K filings (*LOG_WILDFIRE_WORDCNT*) on the wildfire events of firms in the same county of the events versus firms in neighboring counties. The model is:

$$\begin{aligned}
 LOG_WILDFIRE_WORDCNT = & \alpha_0 + \beta_1 WILDFIRE_EVENT_SAME + \beta_2 WILDFIRE_EVENT_NEIGHBOR + \beta_3 \\
 & LOG_MCAP + \beta_4 WEST + \beta_5 TANGIBLE_ASSET + \beta_6 BTM + \beta_7 LEV + \beta_8 ROA + \beta_9 RET + \beta_{10} RET_VOL + \beta_{11} \\
 & LOG_G_SEG + \beta_{12} LOG_B_SEG + \beta_{13} LOG_TOTAL_WORDCNT + YEAR\ FIXED\ EFFECTS + INDUSTRY\ FIXED \\
 & EFFECTS + STATE\ FIXED\ EFFECTS + \varepsilon_{it}
 \end{aligned} \tag{6}$$

LOG_WILDFIRE_DAYCNT_SAME (*D_WILDFIRE_DAYCNT_SAME*) equals to *LOG_WILDFIRE_DAYCNT* (*D_WILDFIRE_DAYCNT*) if a firm experiences wildfire in its headquarter county, and 0 otherwise. *LOG_WILDFIRE_DAYCNT_NEIGHBOR* (*D_WILDFIRE_DAYCNT_NEIGHBOR*) equals to *LOG_WILDFIRE_DAYCNT* (*D_WILDFIRE_DAYCNT*) if a firm experiences wildfire in its MSA but not in its headquarter county, and 0 otherwise. Regression coefficients and t-values (in parentheses) are reported. The standard error estimates are clustered by firm. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, using two-tailed tests. See Appendix 3 for variable definitions. The bolded variables represent the main variables of interest.