THREE ESSAYS ON THE INFLUENCE OF CLIMATE CHANGE ON CORPORATE BEHAVIORS

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Abstract

This dissertation follows the "three papers" dissertation model. It consists of three independent papers but with a related theme focusing on the capital market effects of climate change. The macroeconomic effects of climate change have been well documented in the literature, however, less is known about how climate change influences economic activities at the micro-level. The dissertation fills this gap in and contributes to the literature by exploring the influence of climate disasters on firms' information environment, and the influence of climate change social norms on firms' cash holding behaviors and conditional conservatism.

Chapter 1 "Climate Disasters and Analyst Forecast Properties" examines the relation between climate disasters and firms' information environment. Using analysts' forecast errors and forecast dispersion as proxies for firms' information environment, I find that climate disasters are negatively associated with firms' information environment. I reason that the volatility of ROA and the volatility of cash flows are two potential channels through which climate disasters influence firms' information environment. I also find that the relation between climate disasters and firms' information environment is more pronounced for firms in climate-vulnerable industries. Results from the market reaction tests further support my main findings by documenting that the stock market responds less strongly to positive earnings surprises during periods of high climate disasters. My results are robust to a battery of sensitivity tests, including two-stage least squares (2SLS) approach and a difference-in-differences specification. Overall, the results shed light on the association between climate disasters and firms' information environment, which has significant implications for academics, investors, and standard setters.

In Chapter 2 “Climate Change Social Norms and Corporate Cash Holdings” I study the relationship between climate change social norms (CCSN) and corporate cash holdings for U.S. firms. I find that county-level CCSN is significantly positively associated with cash holdings. My main finding is robust to a battery of robustness tests. Cross-sectional analyses indicate that the positive association between CCSN and cash holdings is more pronounced for financially constrained firms, during periods of heightened media coverage of climate uncertainty, and those with higher climate risk exposures. Overall, my study suggests that county-level CCSN has significant implications for corporate cash holdings.

Chapter 3 “Climate Change Social Norms and Accounting Conservatism” investigates whether climate change social norms influence accounting conservatism. Using data from Yale Climate Opinion Maps over the period 2014-2020, I find that managers of U.S. firms headquartered in counties with higher climate change social norms (CCSN) engage in more conditional conservatism. This result is consistent with the notion that CCSN influences managers’ behavioral intentions towards climate change and thereby shapes their financial reporting choices. Cross-sectional analyses demonstrate that the positive relation between CCSN and conditional conservatism is more pronounced for climate-non-vulnerable industries and during times with greater media coverage of climate change. Given the substitution between accrual-based earnings management (AEM) and real earnings management (REM) as well as managers’ preference for REM, I perform path analysis and find that CCSN directly influences firms’ REM activities and indirectly via conditional conservatism in response to the market pressure arising from climate change. Overall, my findings have timely implications for various financial report users, including standard setters and regulators contemplating new climate-related disclosures.

Overall, these three related papers fill the void in the accounting and finance literature by exploring the micro-level influence of climate change. Specifically, it contributes to a better understanding of the capital market consequences regarding firms' information environment, corporate cash holdings, and accounting practices regarding accounting conservatism and real earnings management.

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Chapter 1: Climate Disasters and Analyst Forecast Properties

1. Introduction

The growing concerns about climate change have attracted much attention in the broad economics literature investigating the impact of climate change on various economic activities (e.g., Dell, Jones, and Olken, 2012; Gallagher and Hartley, 2017; Noy, 2009; Raddatz, 2006). In particular, an emerging strand of literature suggests that climate risk affects capital markets by influencing firm-level economic behaviors and outcomes (e.g., Addoum, Ng, and Ortiz-Bobea, 2020; Hsu, Lee, Peng, and Yi, 2018; Huang, Kerstein, and Wang, 2018; Krueger, Sautner, and Starks, 2020). Somewhat surprisingly, relatively little is known about the impact of climate disasters on firms' information environment. To the extent that firms' information environment plays an important role in affecting capital allocation, especially against the backdrop of climate change, a better understanding of whether and to what extent climate disasters are associated with firms' information environment is particularly important.

Motivated by the gap in the literature, the purpose of this study is to explore whether and to what extent climate disasters are associated with firms' information environment. Prior evidence indicates that firms are directly affected by physical damages inflicted by climate disasters and indirectly affected through the policies and regulations on climate change. Unlike existing studies that typically focus on a certain type of natural disasters (e.g., Kong, Lin, Wang, and Xiang, 2021), I focus specifically on climate disasters because most disaster damages in the U.S. are caused by climate disasters rather than geophysical disasters (CEMHS, 2018; Cutter and Emrich, 2005). In addition, prior studies suggest that climate disasters may have different impacts on economic activities relative to geophysical disasters (e.g., Skidmore and Toya, 2002).

Prior studies suggest that analysts have difficulties dealing with a range of uncertainties and thus are more inclined to issue biased and dispersed forecasts (Amiram, Landsman, Owens, and Stubben, 2018; Hann, Ogneva, and Sapriza, 2012; Mattei and Platikanova, 2017). The magnitude, duration, and economic consequence of climate disasters are extremely difficult for analysts to quantify ex ante. In addition, the consequences of policies and regulations enacted to combat climate change cannot be accurately predicted. As a result, climate disasters exacerbate the forecasting complexity by increasing the volatility of earnings and cash flows, rendering past financial information less relevant and useful. Uncertainty related to both climate risk and transition risk increase the complexity of the forecasting task, in combination with the challenge to prioritize their forecasting task given limited attention and energy (Harford, Jiang, Wang, and Xie, 2019), potentially prevents analysts from incorporating the economic effects of climate disasters into their earnings forecasts in a meaningful and timely manner, thus yielding a deterioration in their analyst forecast accuracy. The situation is further exacerbated due to higher earnings volatility (Huang et al., 2018) and less informative firm disclosure (Ramnath, Rock, and Shane, 2008) linked to potential climate disasters.

Prior research also suggests that the enhanced complexity of forecasting tasks positively impacts forecast dispersion by generating divergent views toward the same climate-induced extreme weather event because different analysts may interpret the same phenomenon in different ways. Based on the above arguments, I predict a positive association between climate disasters and analyst forecast errors and dispersion.

Alternatively, in response to more complex forecasting tasks in high climate disaster periods, analysts are more likely to work harder due to career and reputational concerns (Loh and Stulz, 2018), thus potentially offsetting forecasting challenges imposed by climate disasters.

Moreover, climate uncertainty reduces the optimism bias by making analysts less likely to issue over-optimistic earnings forecasts. In addition, given that some analysts may have difficulty issuing accurate earnings forecasts during periods of high uncertainty arising from climate disasters, it could be an optimal strategy for them to issue forecasts following star/lead analysts. These arguments suggest that climate disasters may not be associated with analyst forecast errors and dispersion. Therefore, whether and how climate disasters are associated with analyst forecast properties is ultimately an empirical question.

I begin by examining the influence of climate disasters on firms' information environment by employing a sample of 382,174 analyst-firm-year observations over the period 2001-2017.[1] To this end, I proxy for firms' information environment using analyst forecast errors and analyst forecast dispersion (Diether, Malloy, and Scherbina, 2002; Hope, 2003; Lang and Lundholm, 1996; Scherbina, 2008). Following the spirit of prior literature (e.g., Eckstein, Lena Hutfils, and Winges, 2019; Huang et al., 2018), I measure the severity of climate disasters as the total amount of annual state-wide monetary property damages caused by climate hazards.

My empirical findings across multiple specifications are consistent with the notion that climate disasters are significantly negatively associated with firms' information environment. My results are also economically meaningful. Specifically, a one standard deviation increase in the severity of climate disasters is related to an increase in forecast errors of 3.05% and an increase in forecast dispersion of 5.25%. This finding suggests that climate disasters could play an important role in shaping firms' information environment.

Having established the negative association between climate disasters and firms' information environment, I next examine whether the relationship is more pronounced for firms

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[1] My data ends in 2017 because this is the latest year when climate disasters data from SHELDUS are available. The release of SHELDUS version 20.0 will take place on February 1, 2022.

belonging to climate-vulnerable industries and the possible channels through which climate disasters influence the information environment. Prior studies (e.g., Huang et al., 2018; Krueger et al., 2020) document that some industries are more susceptible to climate disasters than others. Following Huang et al. (2018), I partition my sample into climate-vulnerable industries and non-climate-vulnerable industries using the Fama French 48 industry classification framework and re-examine my main findings. Consistent with my expectation, I find that the relation between climate disasters and firms' information environment is more pronounced in climate-vulnerable industries. Furthermore, I find that climate disasters increase earnings volatility and cash flow volatility, both of which are likely to further increase the complexity of the forecasting task of analysts, leading to deteriorated firms' information environment.

To further validate my baseline results, I investigate how the stock market responds to earnings surprise around the earnings announcement dates. If climate disasters are positively associated with forecast errors and dispersion indicating higher information asymmetry, I anticipate that market responses are likely to be weaker because investors tend to discount the role of earnings in valuing firms in higher-climate-disaster states (i.e., investors perceive earnings to be noisier). Consistent with my expectations, I find that the positive association between positive earnings surprise and abnormal returns is attenuated due to the influence of climate disasters. In contrast, the market reaction to negative earnings surprise is unlikely to be influenced by climate disasters, consistent with the notion of loss aversion suggested by prospect theory (Kahneman and Tversky, 1979).[2]

To address the potential endogeneity concerns arising from correlated omitted variables, I first employ an instrumental variable approach that uses population density at the state level in the

[2] According to loss aversion, investors have a greater aversion towards losses than equivalent gains, indicating a stronger response to losses than to gains, which is supported by my asymmetrical findings.

U.S. as an instrument for climate disasters (Albouy, Graf, Kellogg, and Wolff, 2016; Huang et al., 2018). The results from the two-stage least squares regressions (2SLS) support my baseline findings. Moreover, I employ the occurrence of Superstorm Sandy as a plausibly exogenous shock and further investigate the potential causal relationship between climate disasters and firms' information environment using a difference-in-differences research design. Furthermore, I mitigate the endogeneity concerns by controlling for additional firm-level and analyst-level characteristics, as well as analyst- and firm-level fixed effects. As anticipated, my main findings continue to hold under all these different model specifications.

I also conduct a battery of sensitivity tests. I use various alternative measures to capture both firms' information environment and climate disasters. Specifically, I follow prior literature and use bid-ask spread and trading volume as two additional proxies for firms' information environment. I proxy for climate disasters using three additional measures: (1) the monetary value of total property and crop damages resulting from climate disasters, (2) the rank of climate disaster damages, and (3) the county-level property damages from all types of climate disasters. Overall, the results show that my baseline findings are robust to all these alternative measures.

Finally, I rule out potential confounding factors that may drive my baseline results. It is plausible that my findings may be caused by observations during the financial crisis periods (Loh and Stulz, 2018), by firms in high climate disaster years (Bourveau and Law, 2021), by firms located in the Gulf Coast states, and by multiple-segment firms. To eliminate these alternative explanations, I drop the corresponding subsamples which are likely to drive my findings. Analyses based on the reduced samples show that the baseline results are robust to all these scenarios, indicating that the effects of climate disasters on firms' information environment are unlikely to be driven by these factors.

This study contributes to the literature in several ways. First, it contributes to a growing body of literature assessing the micro-level economic impact of climate risk (e.g., Addoum et al., 2020; Ding, Liu, Wang, and Wu, 2021; Hsu et al., 2018; Huang et al., 2018) by focusing on the influence of climate disasters on firms' information environment. Specifically, I respond to the research call of Krueger et al. (2020) and explore whether climate disasters in the U.S. influence firms' information environment in terms of higher analyst forecast errors and analyst forecast dispersion. To the best of my knowledge, I am among the first to show that climate disasters are negatively related to firms' information environment, which has significant implications for academics, regulators, as well as investors.

Second, I contribute to the large analyst forecast literature by showing that, although not the focus of my paper, (1) climate disasters are a potential determinant of analyst forecast accuracy and analyst forecast dispersion, and (2) analysts may have difficulties in incorporating environmental uncertainty arising from climate disasters. In this sense, my study complements the established literature on the determinants of analyst forecast properties (e.g., Duru and Reeb, 2002; Hope and Kang, 2005; Zhang, 2006) as well as the literature addressing the relation between analyst forecast properties and uncertainty (e.g., Amiram et al., 2018; Chourou, Purda, and Saadi, 2021; Hann et al., 2012; Hope and Kang, 2005; Mattei and Platikanova, 2017). Unlike previously identified firm-level, industry-level, and market-level determinants, climate disasters are a reasonably exogenous environmental factor that has received scant attention in the analyst forecast literature.

Finally, my paper implicitly responds to the U.S. Securities and Exchange Commission's (SEC) recent initiative in requesting public input on climate-related financial disclosures (SEC, 2021). Given climate disasters worsen corporate information environment, my findings support the view that the rulemaking of the provision of climate-related disclosures may contribute to compensating for the deteriorated corporate information environment caused by the occurrence of climate disasters.

My paper is related to the contemporaneous work of Kong et al. (2021); however, my paper differs from theirs along several different dimensions. First, Kong et al. (2021) focus directly on the effect of disaster events on analyst forecast optimism, while I shed light on the effect of climate disasters on firms' information environment. Second, Kong et al. (2021) focus on earthquakes which tend to cluster in some confined regions. In contrast, I focus on climate disasters, which caused most damages and can occur randomly across the U.S., relative to geophysical hazards. Moreover, it is widely acknowledged that the economic impact of earthquake is likely to be different from that of other climate disasters, as documented in prior economics literature (e.g., Skidmore and Toya, 2002). Third, given that U.S. and emerging economies such as China differ significantly in terms of institutional setup, investor protection, and legal environment, all of which could substantially influence analysts' forecast optimism (Bradshaw, Huang, and Tan, 2019), it is thus very likely that Kong et al. (2021)'s findings may not be extended directly to a U.S. setting.

The remainder of this paper is organized as follows. Section 2 discusses background literature and develops the hypotheses. Section 3 describes the data sources and research design. Section 4 discusses the empirical results, and Section 5 discusses the results of additional analyses and sensitivity checks. Section 6 concludes the study.

2. Background Literature and Hypotheses Development

2.1 The economic impact of climate disasters

Climate change has led to widespread concerns recently. As suggested by the World Economic Forum's Global Risk Report (2020), extreme weather events are ranked as the top risk faced by firms around the globe in the next decade. Globally, disaster damages grew 15-fold from the 1950s to the 1990s (Benson and Clay, 2004) and reached more than $113 billion dollars each year during the 2000s (Rauch, 2012). It is projected that global warming will lead to a significant increase in extreme weather events (IPCC, 2008). As far as the U.S. is concerned, the economic cost of disasters has been steadily increasing, and climate disasters account for most of these damages (CEMHS, 2018; Cutter and Emrich, 2005). As pointed out by Hsiang et al. (2017), it is estimated that a 1-Celsius-degree rise in temperature is associated with a 1.25% decline in GDP in the U.S.

The economic impacts of climate disasters have been well documented in the broad economics literature with mixed findings (e.g., Dell et al., 2012; Gallagher and Hartley, 2017; Raddatz, 2006; Skidmore and Toya, 2002). Dell et al. (2012) find that the negative impacts of temperature on economic growth and export mainly exist in developing countries. Gallagher and Hartley (2017) investigate the impact of hurricane-induced floods on household finance in the U.S. They find that due to the influence of flooding, homeowners are more likely to repay their existing debt using flood insurance rather than to rebuild, leading to a decline in total debts. Raddatz (2006) explores the effects of several kinds of natural shocks, including climate disasters. He finds that climate disasters lead to a roughly 2% decrease in per capita GDP one year following a disaster, but this effect disappears within five years. In contrast, Skidmore and Toya (2002) suggest that geologic disasters are negatively associated with economic growth, whereas climate disasters are positively associated with economic growth.

Although the literature largely focuses on climate disasters at the individual and national levels, an emerging strand of literature examines the firm-level impact of climate risk (e.g., Addoum et al., 2020; Huang et al., 2018; Hsu et al., 2018). Addoum et al. (2020) find that abnormal temperature exposure is inversely associated with earnings at the firm level. Huang et al. (2018) investigate the relation between climate risk and financial performance and financing choices in a global context. Using the climate risk index constructed by Germanwatch based on the number of deaths and economic losses resulting from natural disasters, the authors show that climate risk is negatively associated with financial performance in terms of reduced ROA, increased earnings volatility, and short-term debt, while positively associated with long-term debt. Hsu et al. (2018) investigate the association between natural disasters and firm-level operating performance using the U.S. data. Their findings suggest that firms in states affected by natural disasters are less likely to be profitable than firms in other states.

Overall, despite the sizeable impact of climate disasters at the individual, firm, and country levels, there is limited understanding about how climate disasters are associated with firms' information environment. Given the potential impact of climate change on the capital market, a better understanding of how climate disasters influence firms' information environment is important and has significant implications, not only for capital allocation at the micro level but also for the overall economic growth at the macro level.

2.2 Analyst forecasts as proxies for the information environment

Prior research suggests that analyst forecast properties indicate firms' information environment (Hope, 2003; Horton, Serafeim, and Serafeim, 2013; Lang and Lundholm, 1996). Lang and Lundholm (1996) suggest that firms with better disclosure practices have higher analyst forecast accuracy. Hope (2003) shows that both firm-level disclosures and country-level enforcement are positively associated with higher forecast accuracy. Therefore, I follow the prior literature and proxy for firms' information environment using analyst forecast errors and dispersion (e.g., Horton et al., 2013; Lang and Lundholm, 1996; Lang, Lins, and Miller, 2003; Li and Zaiats, 2017). I argue that an improvement in a firm's information environment is reflected in lower analyst forecast errors and dispersion. In contrast, higher analyst forecast errors and dispersion are indicative of a deterioration in firms' information environment.

2.3 Climate disasters and firms' information environment

I posit that climate disasters are negatively associated with the overall information environment. Prior literature documents evidence on the negative impact of conventional uncertainty on analysts' forecast properties. For example, Hope and Kang (2005) show that macroeconomic uncertainty is negatively associated with analysts' forecast accuracy, with macroeconomic uncertainty proxied by inflation and exchange rate volatility. Zhang (2006) documents that greater information uncertainty can lead to more analyst forecast errors. Unlike conventional uncertainties, uncertainty originating from climate disasters consists of scientific and socio-economic uncertainty (Heal and Millner, 2014).[3] Scientific uncertainty arises from the lack of knowledge to understand the inherently complex nature of climate change, while socio-economic uncertainty stems from a lack of understanding of the economic or social impact of climate change. Scientific and socio-economic uncertainty stemming from climate disasters add much difficulty to analysts' forecasting, thus leading to a noisier information environment.

[3] There is no universally accepted definition of uncertainty. I therefore follow prior literature (e.g., Bloom, 2014) and define it as the difficulty in forecasting the likelihood of unknown outcomes.

The uncertainty inherent in climate disasters increases the complexity of forecasting by affecting firms' earnings volatility (Huang et al., 2018) and corporate disclosure practices (Lehavy, Li, and Merkley, 2011). For example, using a global panel of 55 countries, Huang et al. (2018) suggest that climate risk is positively associated with earnings volatility. Prior literature has identified a negative relation between earnings volatility and earnings predictability (e.g., Dichev and Tang, 2009; Duru and Reeb, 2002). Duru and Reeb (2002), for instance, show that earnings volatility is positively associated with analyst forecast errors. Furthermore, firms may become more conservative and deliberately reduce the quantity and quality of their voluntary disclosures, because of some mitigating effects from competition, litigation risk, and proprietary costs (Hodges, Leatherby, and Mehrotra, 2018; Leuz and Wysocki, 2016). Managers are, therefore, more likely to respond to performance shocks arising from climate disasters by manipulating accounting numbers and disclosures (Gerakos and Kovrijnykh, 2013), reducing the informativeness of disclosures that are normally used by analysts. Consequently, elevated levels of earnings volatility and less informative disclosures exacerbate the challenge of forecasting firms' performance, requiring more efforts from analysts to better understand the effects of climate disasters on firms' earnings.

As economic agents, analysts are subject to limited attention and resources (Harford et al., 2019; Kahneman, 1973). Amiram et al. (2018) suggest that analysts struggle with market-level uncertainty, which leads to greater forecast errors. Consequently, climate disasters that encompass much complexity and uncertainty prevent analysts from assimilating and incorporating climate-related information into earnings forecasts because analysts have difficulties analyzing firms' future financial performance under such a uncertain context (Amiram et al., 2018) or because the costs to do so exceed the benefits (Plumlee, 2003). Taken together, I expect that climate disasters, by increasing the complexity of forecasting task, are positively associated with analysts' forecast errors. I propose my first hypothesis as follows (in alternate form):

H1: Climate disasters are positively associated with analyst forecast errors.

Alternatively, prior literature indicates that analysts' forecast accuracy significantly influences their career upward mobility and reputation (Groysberg, Healy, and Maber, 2011; Hong and Kubik, 2003; Jackson, 2005). Therefore, career and reputational concerns induce analysts to improve their forecast accuracy (Loh and Stulz, 2018).[4] After all, forecast accuracy is one of the most important measures of analyst performance. Furthermore, anecdotal evidence suggests that firms that miss analyst forecasts are likely to experience a significant drop in their stock prices. Consequently, when climate disasters increase, analysts are less likely to issue optimistic forecasts than they do in normal periods, based on career or reputational concerns. The systematic downward bias can enhance their forecast accuracy to some extent (Hugon and Muslu, 2010; Walther and Willis, 2013).[5] In addition, although analysts' tendency to issue optimistic earnings forecasts has been well documented in the literature (e.g., Abarbanell, 1991; Lim, 2001), Keskek and Tse (2018) find that forecasts issued by analysts are much less optimistic for firms in poor information environment. Consequently, climate risk may not be an important factor in influencing analyst forecast accuracy. The above reasoning provides some tension to my hypothesis and justifies the empirical analysis.

[4] There is also a vast literature documenting that analysts are on average optimistically biased to achieve certain goals such as increasing upward mobility and pleasing the management (e.g., Abarbanell, 1991; Lim, 2001). Although analysts are less likely to be penalized for issuing optimistic forecast during high uncertainty periods, continuous opportunistic behaviors are constrained by career and reputational concerns.

[5] Given that my sample is collected in the post-Reg FD period, analysts have less incentives to issue optimistic forecasts to please the firm they covered to obtain private information. However, I acknowledge that there is still some room for analysts to obtain some private information from managers, as suggested by existing studies.

In line with the previous discussion of Hypothesis 1, I argue that climate disasters are associated with not only greater analyst forecast errors but also greater analyst forecast dispersion. Climate disasters are likely to lead to more divergent earnings forecasts because different analysts may interpret the same complex climate-related event in their respective ways, thus engendering disparate views on firms' future performances. In addition, analyst forecasts are more dispersed when the quality and quantity of information disclosed by firms decrease (Healy, Hutton, and Palepu, 1999). Based on the above discussions, I propose my second hypothesis as follows (in alternate form):

H2: Climate disasters are positively associated with analyst forecast dispersion.

In contrast, prior literature documents herding behaviors among financial analysts (e.g., Welch, 2000). Following star/lead analysts would be an optimal strategy for unsophisticated analysts who have fewer resources and are highly concerned with their career prospects. Thus, an enhanced level of climate disasters may encourage analysts to be more conservative and issue forecasts that are less likely to deviate significantly from those issued by star analysts, leading to a relatively lower level of forecast dispersion. As before, these arguments provide some tension to my second hypothesis.

2.4 Climate-vulnerable industries versus non-climate-vulnerable industries

Prior research documents that some industries are more likely to be negatively affected by climate change (Huang et al., 2018; Krueger et al., 2020). Krueger et al. (2020) find that as the exposure to climate change likely varies across industries, the extent to which climate risk is incorporated into equity valuation could vary across industries. Huang et al. (2018) find that firms in climate-vulnerable industries are more susceptible to greater earnings volatility when climate risk increases. Greater earnings volatility inevitably adds an additional layer of difficulty to analysts' work. Therefore, I follow Huang et al. (2018) and partition industries into climate-vulnerable industries and non-climate-vulnerable industries using the Fama French 48 industry classification framework.

I conjecture that analysts will have more difficulty forecasting earnings for firms in climate-vulnerable industries due to the enhanced level of complexity imposed by potential climate disasters. In addition, when a climate disaster strikes, managers from climate-vulnerable industries are more likely to exercise their discretion in financial reporting to meet some specific goals (e.g., meet or beat earnings benchmark). Earnings manipulation in climate-vulnerable industries may further aggravate firms' information environment by leading to deterioration in analysts' performances (e.g., Richardson, 2000; Wilson and Wu, 2011). For example, Wilson and Wu (2011) find that analyst forecast accuracy declines with the level of earnings management. Relative to firms in non-climate-vulnerable industries, firms in climate-vulnerable industries are more likely to suffer from losses when climate-related events strike. In addition, Ciccone (2003) suggests that more disagreement in earnings forecasts occurs following negative news. Based on these discussions, I propose my third hypothesis (in alternate form):

H3: The positive relation between climate disasters and analyst forecast errors (dispersion) is more pronounced for firms in climate-vulnerable industries.

3. Data and Research Design

3.1 Sample selection

The data used in the analysis are compiled from multiple sources: (1) climate disaster data are based on weather-related events from the Spatial Hazard Events and Losses Databases for the United States (SHELDUS) maintained by the Arizona State University; (2) annual earnings analyst forecast data are from Institutional Brokers Estimate System (I/B/E/S) detail U.S. file; (3) financial data are from Compustat, and (4) stock price data are from Center for Research in Security Prices (CRSP). My sample starts from 2001 because this is the first year when the Regulation Fair Disclosure (hereafter Reg FD)[6] took into effect and ends in 2017 because this is the latest year when climate disasters data from SHELDUS are available.

In line with the prior literature on security analysts (e.g., Clement and Tse, 2005), I employ several filters to derive the final sample. I eliminate all observations with missing information on the forecast announcement date, earnings announcement date, forecast value, actual value, and firm ticker. I delete observations for which the forecast announcement date is later than the earnings announcement date. In addition, to be included in my sample, a firm is required to have at least three observations in a specific year to construct analyst forecast dispersion. Following prior research, I retain the last earnings forecast issued by each analyst before fiscal year-end for each firm and eliminate observations with unidentified analysts. In terms of the financial statement data and stock price data, I delete all observations with missing or negative information on total assets and stock prices, and all observations with stock prices less than one dollar.

Finally, I merge the firm-level financial data with the state-level climate disasters data based on the locations of firms' headquarters. The intersection of these data sets leads to a final sample consisting of 382,471 firm-analyst-year observations, representing 11,975 analysts and 4,845 distinct firms over the period 2001-2017. Table 1 reports the sample distribution by state and year. As shown in Table 1, California has the largest number of observations (74,141), followed by Texas (44,212), New York (28,567), Massachusetts (21,003), Illinois (18,247), and

[6] Reg FD was passed in 2000 to prohibit firms from disclosing private information to market participants such as security analysts. Given that the private information disclosed by managers to analysts may influence their forecast accuracy as indicated in the prior literature, limiting my sample to the post-Reg FD period can eliminate the distortion caused by private disclosures.

Pennsylvania (15,726), while at the lower end are Alaska (88), Wyoming (133), and New Mexico (185).

Table 1: Sample distribution by state and year

State	Year																	
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Total
AK	5	6	4	5	12	13	8	8	5	5	5	5	4	3	0	0	0	88
AL	75	53	69	77	148	151	153	158	139	144	177	182	183	158	153	155	148	2323
AR	98	166	141	159	147	135	114	119	123	124	130	126	125	160	157	160	159	2343
AZ	260	326	372	363	384	408	398	393	364	366	378	298	328	359	293	310	328	5928
CA	2652	3555	3725	3990	4536	4494	4494	4405	4255	4427	4636	4673	4786	4958	4865	4847	4843	74141
CO	270	290	347	357	377	339	391	406	418	493	563	632	660	658	681	634	670	8186
CT	187	203	254	246	253	300	306	303	319	326	370	419	431	437	483	520	482	5839
DC	58	84	101	111	132	131	130	96	76	93	87	98	111	96	108	97	81	1690
DE	67	54	57	61	83	79	77	72	65	69	58	72	68	67	78	71	62	1160
FL	455	497	564	639	736	803	835	822	813	835	863	838	921	1003	1030	1025	964	13643
GA	295	399	473	492	611	555	547	517	510	598	632	587	688	729	711	705	765	9814
HI	6	4	5	8	19	15	17	21	19	29	45	57	58	55	52	56	51	517
IA	40	63	74	88	101	98	97	95	98	89	89	92	96	95	106	109	102	1532
ID	35	51	64	70	70	47	48	39	45	47	54	65	59	65	62	58	66	945
IL	644	635	744	718	882	946	1016	1022	1056	1124	1210	1346	1415	1373	1372	1391	1353	18247
IN	109	132	157	156	239	228	235	243	252	287	308	334	356	388	436	397	372	4629
KS	86	116	128	79	83	60	88	93	84	83	87	79	119	112	140	159	163	1759
KY	68	105	120	128	157	129	130	168	164	192	176	169	189	183	176	165	170	2589
LA	142	146	105	87	105	170	178	202	190	207	163	144	122	108	130	123	135	2457
MA	835	838	916	1055	1160	1245	1220	1265	1190	1257	1271	1367	1314	1464	1525	1471	1610	21003
MD	174	209	273	276	354	388	363	412	409	445	460	405	383	376	333	387	361	6008
ME	7	4	6	6	7	6	7	8	9	15	17	14	23	22	31	31	28	241
MI	336	341	307	297	380	406	442	402	392	400	450	415	449	458	454	494	471	6894
MN	264	391	481	505	567	577	579	606	584	539	559	564	536	542	556	511	456	8817
MO	268	309	315	302	352	327	334	327	357	376	420	457	470	476	437	452	410	6389
MS	0	3	5	13	34	36	30	40	61	64	59	48	49	50	54	52	55	653
MT	4	4	7	6	41	47	48	41	33	12	6	11	6	0	0	7	7	280
NC	261	341	338	370	458	470	495	485	511	512	581	576	593	627	598	609	598	8423
ND	0	0	13	9	8	12	11	13	13	15	16	14	22	20	20	16	14	216
NE	23	37	43	47	58	69	69	86	126	158	158	149	147	164	160	161	122	1777
NH	26	33	31	30	27	31	26	21	29	27	19	43	42	31	33	40	39	528
NJ	455	539	599	703	792	748	801	700	693	767	829	804	849	859	823	835	849	12645
NM	5	6	6	9	20	19	17	20	13	13	11	8	6	5	7	9	11	185
NV	114	154	202	232	213	264	236	238	225	264	293	266	234	207	161	168	181	3652
NY	889	1069	1119	1165	1437	1552	1645	1670	1657	1843	1950	2097	2056	2106	2087	2140	2085	28567
OH	450	510	521	505	684	714	700	667	677	752	788	867	919	913	943	942	963	12515
OK	131	146	156	149	162	194	206	268	260	259	295	309	386	425	460	425	434	4665
OR	157	189	230	230	282	268	238	240	201	213	231	247	246	232	213	162	150	3729
PA	540	577	701	687	878	994	1021	988	979	1008	1035	1048	1016	1036	1111	1078	1029	15726
PR	0	0	0	0	13	12	5	11	9	7	10	17	22	32	29	31	31	229
RI	72	62	59	68	84	81	79	93	87	97	100	90	95	97	111	119	112	1506
SC	38	34	33	39	95	102	105	96	93	91	91	94	103	130	131	135	142	1552
SD	5	17	18	21	19	17	42	19	14	18	20	19	21	15	16	27	31	339
TN	294	348	377	402	423	440	388	427	428	483	454	474	484	483	512	487	503	7407
TX	1407	1782	1846	1913	2188	2339	2349	2496	2489	2511	2721	2886	3281	3393	3651	3579	3381	44212
UT	28	44	74	110	150	144	143	149	138	153	169	178	186	140	144	146	141	2237
VA	410	387	506	548	567	619	612	560	573	607	627	559	559	530	580	605	596	9445
VT	24	18	21	22	20	21	8	7	7	10	11	9	8	0	7	9	7	209
WA	286	283	412	442	517	568	568	571	568	586	606	605	621	589	582	590	624	9018
WI	174	186	220	230	275	276	288	323	312	319	308	322	338	336	350	354	326	4937
WV	0	5	7	6	27	32	37	43	49	60	49	41	43	35	27	21	22	504
WY	0	0	0	0	0	0	0	0	0	13	20	19	25	20	16	10	10	133
Total	13229	15751	17346	18231	21367	22119	22374	22474	22181	23432	24665	25238	26251	26820	27195	27085	26713	382471

3.2 Measure of climate disasters

I derive my measure of the severity of climate disasters using the weather-related climate disaster data from SHELDUS database for each state and year (CEMHS, 2018). I adopt the state-level measure to avoid the potential limitation of the SHELDUS data (i.e., country-level data are averaged out) because it is highly unlikely that all counties are equally affected by the same disaster, as suggested by Gall, Borden, and Cutter (2009).[7] The SHELDUS database covers county-level

[7] As pointed out by Gall et al. (2009), one potential limitation of the SHELDUS data is that economic losses are equally distributed across counties if they are simultaneously impacted by a climate event. Put it differently, using the county-level data is based on the tenuous assumption that all counties are equally affected by the same climate disaster.

natural disaster losses resulting from a group of 18 different categories of natural hazards, such as hurricanes, droughts, floods, and tornados. In calculating my measure of climate disasters, I focus on weather-related events and exclude geophysical disaster events in my analysis.[8] For each climate disaster event recorded in SHELDUS, I collect data on the date of the event and monetary property losses related to that event.[9] Following the spirit of the prior literature (e.g., Eckstein et al., 2019; Miao, Hou, and Abrigo, 2018), I proxy for the severity of climate disasters by summing the total amount of annual state-wide monetary property damages (constant 2017 US dollars) caused by climate hazards and denote it as CDP. Thus, the increasing magnitude of CDP indicates a higher level of climate disaster risk.

Table 2 shows the climate disasters proxied by the total annual climate disaster property damages (in millions of U.S. dollars) at the state level from 2001 to 2017. Texas has the highest climate damage with estimated property damages of 106,345 million U.S. dollars over 2001-2017, followed by Louisiana (64,176), Florida (33,189), and Mississippi (27,271), all situated in the Gulf Coast.

However, adopting a state-level climate disasters measure can avoid this potential drawback. As a robustness test, I also replicate my regression using the county-level measure and the results (which are reported in Section 5.2.3) are qualitatively unchanged.

[8] As mentioned earlier, one of the reasons why I focus on climate disasters rather than geophysical disasters is that prior studies suggest that climate disasters may have a different impact on economic activities relative to geophysical disasters (e.g., Skidmore and Toya, 2002). Thus, my study covers a total of 13 types of climate-related events including coastal events, drought, flooding, hail, heat, hurricane, landslide, lightning, severe storm, tornado, wildfire, wind, and winter weather. Geophysical natural hazards, such as earthquake and volcano, are excluded from the analysis. In fact, there was no major earthquake or volcano eruptions taking place over the period 2001-2017 in the mainland U.S.

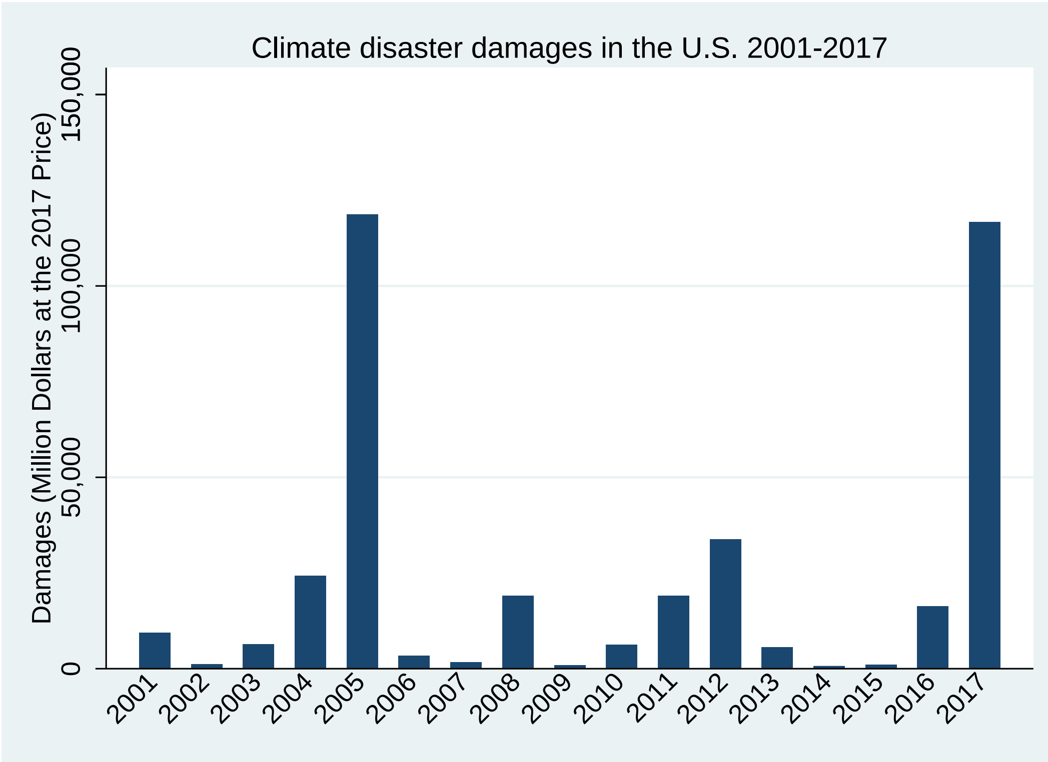
[9] Although employing a single index can potentially camouflage the heterogeneity in the effects of disparate disasters, arguably total economic damages is one of the most important indicators in evaluating the severity of natural disasters. For example, Eckstein et al. (2019) create a global climate risk index (including the U.S.) in which economic losses and the number of deaths are the main factors in constructing the index. In addition, unlike Miao et al. (2018) who focus on the total of crop and property damages when investigating the dynamic fiscal response to natural disasters, I focus only on property damages in my baseline regressions because firms are mostly concerned with property economic damages rather than crop damages. However, as a robustness test, I also construct a new measure which includes both property and crop damages.

Table 2: Total annual disaster property damages by state over 2001-2017(in million U.S. dollars)

State	Code	Total property damages	State	Code	Total property damages
ALABAMA	AL	8180.15	MONTANA	MT	19.84
ALASKA	AK	2.48	NEBRASKA	NE	895.21
ARIZONA	AZ	2894.01	NEVADA	NV	44.56
ARKANSAS	AR	1463.97	NEW HAMPSHIRE	NH	19.05
CALIFORNIA	CA	4544.62	NEW JERSEY	NJ	25376.66
COLORADO	CO	4067.83	NEW MEXICO	NM	456.65
CONNECTICUT	CT	94.0115	NEW YORK	NY	2241.08
DELAWARE	DE	33.64	NORTH CAROLINA	NC	1885.89
DISTRICT OF COLUMBIA	DC	0.03	NORTH DAKOTA	ND	15.31
FLORIDA	FL	33189.29	OHIO	OH	1113.42
GEORGIA	GA	798.27	OKLAHOMA	OK	3909.66
HAWAII	HI	0	OREGON	OR	0.70
IDAHO	ID	486.14	PENNSYLVANIA	PA	1383.88
ILLINOIS	IL	1844.10	PUERTO RICO	PR	19012.50
INDIANA	IN	948.643	RHODE ISLAND	RI	99.48
IOWA	IA	8040.71	SOUTH CAROLINA	SC	399.37
KANSAS	KS	715.66	SOUTH DAKOTA	SD	4.49
KENTUCKY	KY	544.74	TENNESSEE	TN	4835.65
LOUISIANA	LA	64175.74	TEXAS	TX	106344.90
MAINE	ME	46.10	UTAH	UT	0.70
MARYLAND	MD	732.11	VERMONT	VT	815.00
MASSACHUSETTS	MA	240.28	VIRGINIA	VA	906.00
MICHIGAN	MI	599.66	WASHINGTON	WA	14.45
MINNESOTA	MN	231.11	WEST VIRGINIA	WV	366.33
MISSISSIPPI	MS	27270.65	WISCONSIN	WI	1944.16
MISSOURI	MO	5033.61	WYOMING	WY	12.31

I also provide a snapshot of the annual total property damages caused by weather-related disasters over the period of 2001-2017 in Figure 1. As can be visualized from Figure 1, Year 2005 has the highest climate disaster losses with an estimated damage of 118,732 million U.S. dollars because of Hurricane Katrina, which is the most destructive climate disaster event in the U.S. history. It is worth noting that climate disaster risk has been increasing in recent years and peaked in the Year 2017 with an estimated damage of 116,693 million U.S. dollars, suggesting an increasingly devastating power of climate disasters.

Figure 1: Trends in climate disaster damages in the U.S., 2001-2017



3.3 Measures of firms' information environment

Given the critical role of security analysts in the capital market in terms of disseminating, monitoring, and providing firm-level financial information, I proxy for firms' information environment with analyst forecast errors and analyst forecast dispersion (Diether et al., 2002; Hope, 2003; Lang and Lundholm, 1996; Scherbina, 2008). Following the prior literature, I measure analyst forecast errors using the following formula:

$$AFE_{a,i,t} = 100 * \frac{|Forecast_{a,i,t} - Earnings_{i,t}|}{Price_{i,t}}$$

where $Forecast_{a,i,t}$ is the latest analyst forecast issued by analyst a for firm i for period t before earnings announcements, $Earnings_{i,t}$ is the actual value released on the earnings announce date for firm i for period *t*, and $Price_{i,t}$ is the stock price for firm i at the forecast date. As in prior research, I measure analyst forecast dispersion using the standard deviation of analyst forecast values for a given firm scaled by the stock prices at the beginning of each year.

3.4 Empirical Methodology

I estimate the impact of climate disasters on firms' information environment using the following model:

$$\begin{aligned} FIE_{ait} = {} & \beta_0 + \beta_1\, CDP_{it} + \beta_2\, Size_{it} + \beta_3\, Loss_{it} + \beta_4\, ROA_{it} + \beta_5\, MTB_{it} + \beta_6\, Sgrowth_{it} \\ & + \beta_7\, Age_{it} + \beta_8\, SDret_{it} + \beta_9\, HOR_{ait} + \beta_{10}\, NOA_{it} + \beta_{11}\, NOC_{ait} + \beta_{12}\, NOF_{ait} \\ & + \alpha_y + \alpha_{ind} + \alpha_{sta} + \varepsilon_{ait} \qquad (1) \end{aligned}$$

where subscripts *a*, *i*, and *t* refer to analyst, firm, and year, respectively. α_y , α_{ind} and α_{sta} are year, industry, and state fixed effects, respectively. I proxy for firms' information environment (henceforth *FIE*) using analyst forecast errors (henceforth *AFE*) and analyst forecast dispersion (henceforth *DISP*). CDP denotes for climate disaster property damages, which is measured by the total amount of annual state-wide monetary property damages caused by climate hazards. My variable of interest in equation (1) is *CDP*. I predict that the coefficient on *CDP* will be positive, implying that climate disasters cause deterioration of firms' information environment.

When estimating equation (1), I include a wide set of control variables that could potentially affect firms' information environment.[10] Prior research (e.g., Duru and Reeb, 2002; Mattei and Platikanova, 2017) indicates that firm size and firm age are associated with more accurate analyst forecasts and less analyst forecast dispersion. I include firm size which is proxied by the natural logarithm of total assets, and firm age proxied by the number of years since a firm first appeared in the Compustat database. Following the extant literature, I control for other firm-level characteristics such as *ROA*, whether a firm is a loss firm (*Loss*), the market to book ratio (*MTB*), and sales growth (*Sgrowth*) in the model. Other than firm-level attributes, I also control for some analyst-level characteristics which prior literature identifies as determinants of firms' information environment (Harford et al., 2019). Prior literature shows that the number of analysts following a firm is positively associated with analyst forecast accuracy. I therefore include the number of analysts following a firm (*NOA*). In addition, I include the variable of *Horizon*, which is defined as the distance between the earnings forecast issuance date and the actual earnings announcement date. I measure the complexity of analysts' task using the number of firms they follow (*NOC*) and the number of earnings forecasts issued by an analyst (*NOF*). To control for time-invariant industry-, year-, and state-level characteristics, I control for industry-, year-, and state-level fixed effects. I winsorize all continuous variables at the top and bottom percentiles to eliminate the effects of outliers. I double cluster standard errors at the state and analyst levels to control for potential cross-sectional correlation.

[10] Detailed definitions of each variable used in this study can be found in the Appendix.

4. Empirical Results

4.1 Descriptive statistics

Table 3 reports the descriptive statistics and pairwise correlations for the variables used in the baseline regression models. As shown in Panel A of Table 3, the mean (median) for analyst forecast errors and analyst forecast dispersion are 0.766 (0.164) and 0.008(0.003), respectively, which are largely consistent with those reported in the prior literature. The fact that the mean (median) of the property damages resulting from climate disasters is 570.04 (3.87) million U.S. dollars and that the standard deviation of property damages is 2810.89 million U.S. dollars suggests significant variation in climate disasters across the sample.

Table 3 Panel B reports the pairwise correlations between the variables used in my main analysis. It is worthwhile to note that: (1) climate disasters are positively and significantly correlated with both analyst forecast errors and analyst forecast dispersion, and (2) analyst forecast errors are positively and significantly correlated with analyst forecast dispersion.

Table 3: Summary statistics and Pairwise correlations

Panel A: Summary statistics

	N	Mean	Std. Dev.	p25	Median	p75
AFE	382354	.766	2.021	.052	.164	.524
DISP	382453	.008	.017	.001	.003	.007
CDP	382471	570.04	2810.89	0	3.87	76.55
Size	382471	7.965	1.86	6.61	7.895	9.196
Loss	382471	.203	.402	0	0	0
ROA	382471	.027	.119	.008	.043	.083
MTB	382458	3.352	5.55	1.515	2.476	4.133
Sgrowth	382471	.128	.3	-.004	.079	.196
Age	382471	26.876	20.007	11	20	39
SDret	382340	.027	.019	.015	.021	.032
Horizon	382471	116.098	88.301	62	98	122
NOA	382471	18.745	11.156	10	17	25
NOC	382471	16.617	8.666	11	16	21
NOF	382471	4.164	2.577	2	4	5

Panel B: Pairwise correlations (* significant at the 1% level)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) AFE	1.000													
(2) DISP	0.672*	1.000												
(3) CDP	0.016*	0.031*	1.000											
(4) Size	-0.113*	-0.119*	0.026*	1.000										
(5) Loss	0.337*	0.420*	0.003	-0.287*	1.000									
(6) ROA	-0.300*	-0.376*	0.004*	0.257*	-0.694*	1.000								
(7) MTB	-0.089*	-0.110*	-0.018*	-0.050*	-0.001	0.030*	1.000							

(8) Sgrowth	-0.031*	-0.055*	0.057*	-0.139*	-0.008*	-0.023*	0.107*	1.000						
(9) Age	-0.070*	-0.079*	-0.003	0.577*	-0.200*	0.151*	-0.054*	-0.199*	1.000					
(10) SDret	0.304*	0.371*	-0.027*	-0.337*	0.339*	-0.316*	-0.044*	0.047*	-0.261*	1.000				
(11) Horizon	0.168*	0.031*	0.011*	-0.111*	0.053*	-0.061*	0.003	0.003	-0.064*	0.047*	1.000			
(12) NOA	-0.140*	-0.111*	0.037*	0.561*	-0.096*	0.161*	0.098*	-0.012*	0.152*	-0.130*	-0.073*	1.000		
(13) NOC	-0.005*	0.013*	0.045*	0.098*	-0.020*	-0.006*	-0.015*	-0.013*	0.072*	-0.071*	-0.099*	0.004*	1.000	
(14) NOF	-0.043*	0.060*	0.034*	0.176*	-0.009*	0.036*	-0.037*	-0.033*	0.088*	-0.020*	-0.473*	0.169*	0.130*	1.000

4.2 Baseline regression results

I report my baseline regression results on the relation between climate disasters and firms' information environment in Table 4. Columns (1) and (2) of Table 4 report the relation between climate disasters and firms' information environment proxied by analyst forecast errors after controlling for firm-level characteristics and analyst-level characteristics, respectively. Column (3) reports my baseline regression result.

As indicated in Table 4 Panel A, I find and document that climate disasters are positively and significantly related to firms' information environment across different specifications (coefficients range from 0.837 to 0.992). Specifically, I find that the coefficient on *CDP* is positive and statistically significant (coef. =0.837, t-stat. =7.09) at the 1% level in my baseline regression model. In terms of economic magnitude, a one standard deviation increase in climate disasters is associated with a 3.05 % increase in analyst forecast errors.[11] This represents an increase of 0.023 in forecast errors for an average forecast error of 0.766. The signs of the coefficients on control variables are largely in line with those in the prior literature. Overall, the finding is consistent with H1, which states a positive association between climate disasters and analyst forecast errors.

Turning to Panel B of Table 4, I examine the relation between climate disasters and firms' information environment proxied by analyst forecast dispersion. Similarly, Columns (4) and (5) of

[11] The impact of a one standard deviation increase in climate disaster risk on firms' information environment in terms of analyst forecast errors is calculated as:1.0e-11∗0.837(coefficient reported in Table 4 Column (3)) *2810.89e+06 (standard deviation of climate disaster risk as reported in Table 3)/0.766(mean of forecast errors as reported in Table 3) =3.05%.

Table 4 report the relation between climate disasters and firms' information environment, proxied by analyst forecast dispersion after controlling for firm-level characteristics and analyst-level characteristics, respectively. Column (6) reports my baseline regression result for analyst forecast dispersion.

An overview of my findings shows that climate disasters are positively and significantly associated with analyst forecast dispersion across specifications (coefficients range from 0.014 to 0.016). Specifically, I find that the coefficient on *CDP* is positive and statistically significant (coef. =0.015, t-stat. =4.97) at the 1% level in the baseline regression model. In terms of economic magnitude, a one standard deviation increase in climate disasters is associated with an increase in forecast dispersion of 5.25%.[12] This represents an increase of 0.0004 in forecast dispersion for an average forecast dispersion of 0.008. My finding is consistent with H2, which states a positive association between climate disasters and analyst forecast dispersion.

Overall, the finding, indicating a positive and significant association between climate disasters and analyst forecast errors and dispersion, suggests that climate disasters are significantly negatively associated with firms' information environment.

Table 4: Relation between climate disasters and firm's information environment: Baseline OLS regression results

	(1)	(2) Panel A AFE	(3)	(4)	(5) Panel B DISP	(6)
CDP	**0.846***** **(6.93)**	**0.992***** **(7.42)**	**0.837***** **(7.09)**	**0.014***** **(5.28)**	**0.016***** **(3.79)**	**0.015***** **(4.97)**
Size	-0.022* (-1.88)		0.103*** (8.21)	0.000 (1.30)		0.001*** (6.41)
Loss	1.088*** (8.28)		1.113*** (8.17)	0.011*** (9.62)		0.011*** (9.45)
ROA	-1.470***		-1.336***	-0.019***		-0.018***

[12] The impact of a one standard deviation increase in climate disaster risk on firms' information environment in terms of analyst forecast dispersion is calculated as:1.0e-11 ∗ 0.015(coefficient reported in Table 4 Column (6)) * 2810.89e+06 (standard deviation of climate disaster risk as reported in Table 3)/0.008(mean of forecast dispersion as reported in Table 3) =5.25%.

	(-5.07)		(-4.95)	(-6.76)		(-6.67)
MTB	-0.018***		-0.014***	-0.000***		-0.000***
	(-5.47)		(-4.68)	(-4.90)		(-4.55)
Sgrowth	-0.197***		-0.154***	-0.003***		-0.003***
	(-3.25)		(-2.90)	(-5.62)		(-5.53)
Age	0.000		-0.001	0.000		-0.000
	(0.36)		(-1.52)	(0.47)		(-0.80)
SDret	23.824***		23.835***	0.253***		0.253***
	(12.88)		(12.41)	(13.14)		(13.00)
Horizon		0.004***	0.004***		0.000***	0.000***
		(20.07)	(17.65)		(14.38)	(11.21)
NOA		-0.030***	-0.023***		-0.000***	-0.000***
		(-12.46)	(-8.50)		(-16.43)	(-9.18)
NOC		-0.001	-0.001		-0.000	-0.000
		(-0.55)	(-0.60)		(-0.14)	(-0.02)
NOF		0.032***	0.012**		0.001***	0.000***
		(4.63)	(2.16)		(10.98)	(9.38)
Constant	0.199	0.703***	-0.814***	-0.001	0.009***	-0.005***
	(1.32)	(8.29)	(-6.71)	(-0.51)	(16.73)	(-4.46)
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes
N	382321	382354	382321	382303	382336	382303
R^2	0.1970	0.0985	0.2272	0.2951	0.0935	0.3006

This table presents the regression results of the relation between climate disasters and firms' information environment. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

4.3 Climate-vulnerable industries versus non-climate-vulnerable industries

Prior literature documents the disproportionate impact of climate change on firms in climate-vulnerable industries as opposed to non-climate-vulnerable industries (Huang et al., 2018; Krueger et al., 2020). I extend my analysis by focusing on the potential heterogeneous impact of climate disasters on firms' information environment in different industries.

In my research context, both analyst forecast errors and analyst forecast dispersion are influenced by the uncertainty associated with climate disasters. Compared to analyst forecasts for firms in non-climate-vulnerable industries, analyst forecasts for firms in climate-vulnerable industries are more likely to be influenced by climate disasters. Following Huang et al. (2018), I classify Agriculture, Business Services, Communication, Energy, Food Products, Health Care, and Transportation as climate-vulnerable industries while the rest are classified as non-climate-vulnerable industries. I drop the industry fixed effects because the indicator variable *Vulnerability* partially captures the industry fixed effects.[13] All other variables employed in the analysis are the same as those specified in the baseline regression model.

I present the regression results in Table 5. As predicated, I find that the coefficients on the interaction terms between climate disasters and vulnerability are positive and statistically significant for both analyst forecast errors (coef. =0.926, t-stat. =4.01) and analyst forecast dispersion (coef. =0.017, t-stat. =8.10) at the 1% level. These findings indicate that industry vulnerability moderates the relation between climate disasters and firms' information environment, and that the negative relation between climate disasters and firms' information environment is more pronounced for firms in climate-vulnerable industries, thus lending support to H3.

Table 5: Relation between climate disasters and firms' information environment: Impact of climate vulnerability

	(1) AFE	(2) DISP
CDP	0.474***	0.008***
	(2.80)	(4.78)
Vulnerability	-0.021***	-0.000***
	(-2.95)	(-7.16)
CDP* Vulnerability	**0.926*** **	**0.017*** **
	(4.01)	**(8.10)**
Size	0.144***	0.001***
	(43.53)	(40.65)
Loss	1.122***	0.011***

[13] My results are qualitatively unchanged if I include industry fixed effects in the model.

	(66.14)	(84.12)
ROA	-1.392***	-0.018***
	(-22.62)	(-34.61)
MTB	-0.017***	-0.000***
	(-30.12)	(-40.05)
Sgrowth	-0.134***	-0.003***
	(-8.27)	(-18.03)
Age	-0.002***	-0.000***
	(-9.69)	(-6.73)
SDret	24.291***	0.257***
	(57.02)	(69.66)
Horizon	0.004***	0.000***
	(74.81)	(23.79)
NOA	-0.025***	-0.000***
	(-65.38)	(-49.45)
NOC	0.000	0.000***
	(0.76)	(2.90)
NOF	0.022***	0.000***
	(16.63)	(38.21)
Constant	-1.154***	-0.008***
	(-38.20)	(-32.08)
Year	Yes	Yes
State	Yes	Yes
N	382321	382303
R^2	0.2154	0.2855

This table presents the regression results of the relation between climate disasters and firms' information environment for firms in climate-vulnerable industries and non-climate-vulnerable industries classified based on the Fama French 48 industry framework. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

4.4 Potential economic channels

Having established the negative relationship between climate disasters and firms' information environment, I provide further evidence by examining the potential channels through which climate disasters may influence firms' information environment. Regarding my first channel, I exploit the link between climate disasters and the volatility of firms' performance in terms of ROA. I posit that climate disasters are positively associated with the volatility of ROA, making analyst forecast more difficult and engendering divergent interpretations regarding firms' future performances. In a similar vein, the second channel, the volatility of cash flows, can also result from the occurrence of climate disasters and complicates analysts' forecasting job, leading to deterioration in analyst forecast quality. To test my conjectures, I estimate the equation (1), with the dependent variable being either the volatility of *ROA* (*ROA_SD*) or the volatility of cash flows (*CF_SD*). My variable of interest is still *CDP*.

Table 6 presents the results. I find that the coefficients on *CDP* are significant at the 1% level (coef. =0.064, t-stat. =3.15; coef. =0.074, t-stat. =4.81) for both models, suggesting that climate disasters increase the volatility of both *ROA* and cash flows. These findings indicate that the volatility of *ROA* and cash flows are two potential channels through which climate disasters influence analyst forecast properties.

Table 6: Channel analysis

	(1) ROA_SD	(2) CF_SD
CDP	**0.064*** (3.15)**	**0.074*** (4.81)**
Size	-0.006*** (-14.93)	-0.018*** (-9.75)
Loss	0.011*** (7.12)	0.009** (2.53)
ROA	-0.011* (-1.76)	-0.118*** (-5.60)
MTB	0.000 (1.11)	0.000 (0.46)
Sgrowth	-0.002 (-1.52)	0.017** (2.67)
Age	0.000*** (3.89)	0.000** (2.39)
SDret	0.141*** (9.61)	0.080 (1.56)
Horizon	0.000** (2.66)	-0.000 (-0.32)
NOA	0.000*** (3.90)	0.001*** (7.59)

NOC	0.000	0.000**
	(0.86)	(2.06)
NOF	0.000***	0.000***
	(4.44)	(3.82)
Constant	0.060***	0.150***
	(23.23)	(13.57)
Industry	Yes	Yes
Year	Yes	Yes
State	Yes	Yes
N	341303	336782
R2	0.2135	0.2112

This table presents the regression results of the channel analysis. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

4.5 Corroborating evidence from earnings surprise and market reaction tests

I further validate the relationship between climate disasters and firms' information environment by implementing a market reaction test that is similar in spirit to that of Nagar, Schoenfeld, and Wellman, (2019). I conjecture that when the likelihood of climate disasters is high, investors' responses to earnings surprises are weaker because they discount the usefulness of earnings in valuing firms. In contrast, if investors view earnings as a more valuable tool to value firms, the market response tends to be stronger. Specifically, I use the following model to test the market reaction:

$$CAR(-1,1)_{it} = \beta_0 + \beta_1\, CDP_{it} + \beta_2\, Sur_{it} + \beta_3\, CDP_{it} * Sur_{it} + \beta_4\, Size_{it} + \beta_5\, Loss_{it} + \beta_6\, ROA_{it} + \beta_7\, MTB_{it} + \beta_8\, Sgrowth_{it} + \beta_9\, Age_{it} + \beta_{10}\, SDret_{it} + \alpha_y + \alpha_f + \varepsilon_{ait} \qquad (2)$$

where subscripts *i* and *t* refer to firm and year, respectively. The dependent variable *CAR* (-1,1) is the cumulative market-adjusted abnormal returns over a three-day event window (-1, 1) centered on the earnings announcement date. I measure earnings surprises as the difference between actual earnings and analyst consensus mean earnings forecasts.[14] The independent variable of interest is the interaction term between *CDP* and *Sur*. I predict that the coefficient on the interaction term will be negative, suggesting that the magnitude of market response is mitigated when climate disaster risk is high. Specifically, I examine whether market reaction depends on the type of earnings news by partitioning earnings surprises into positive and negative ones.

Consistent with the prior literature (e.g., Nagar et al., 2019), in my simplest specifications, the results reported in Columns (1), (2), and (4) in Table 7 indicate that the coefficients on earnings surprise are positive and statistically significant at the 5% level (coef. =0.002, t-stat. =1.98; coef. =0.005, t-stat. =2.48) and at the 1% level (coef. =0.003, t-stat. =3.35), respectively, suggesting that, as expected, the market responds positively to positive earnings surprise and negatively to negative earnings surprise.

More importantly, in line with my expectation, I find that the coefficient on the interaction term is negative and statistically significant at the 5% level (coef. =-0.441, t-stat. =-2.42), suggesting that the market response to positive earnings surprise is less pronounced for firms headquartered in high climate disaster states, due to investors tending to discount the role of earnings in valuing firms in these states. This finding implies that investors do not expect analyst forecasts to be accurate when the possibility of climate disasters is high, further corroborating my baseline findings. In contrast, I find that the coefficient on the interaction term is insignificant at the conventional level (coef. =0.055, t-stat. =0.88) for negative earnings surprise. This finding implies that the negative market response to negative earnings surprise is less likely to be affected by climate disasters, which is consistent with the concept of loss aversion suggested by prospect theory (Kahneman and Tversky, 1979).

[14] Untabulated results show that my findings are robust to: (1) using a number of alternative windows such as (-3, 3), (0, 1), and (0, 3), and (2) using the median earnings forecast to calculate the earnings surprises.

Table 7: Market reaction tests

	(1) Sur	(2) Sur>=0	(3) Sur>=0	(4) Sur<0	(5) Sur<0
CDP		0.075*	0.076*	-0.014	-0.018
		(1.93)	(1.95)	(-0.29)	(-0.38)
Sur	0.002**	0.005**	0.005**	0.003***	0.002***
	(1.98)	(2.48)	(2.53)	(3.35)	(3.19)
CDP*Sur		**-0.423****	**-0.441****	**0.065**	**0.055**
		(-2.35)	**(-2.42)**	**(1.03)**	**(0.88)**
Size			-0.007***		-0.011***
			(-2.96)		(-3.59)
Loss			-0.004		-0.000
			(-1.16)		(-0.13)
ROA			-0.046***		-0.001
			(-2.67)		(-0.04)
MTB			-0.000		-0.000
			(-0.32)		(-1.07)
Sgrowth			0.007*		0.004
			(1.78)		(1.00)
Age			-0.000		-0.001**
			(-0.49)		(-2.09)
SDret			0.147**		-0.032
			(2.03)		(-0.47)
Constant	0.004***	0.016***	0.070***	-0.014***	0.095***
	(7.11)	(23.86)	(3.35)	(-16.68)	(3.61)
Firm	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	29635	16691	16683	11638	11624
R^2	0.1643	0.2194	0.2216	0.2703	0.2720

This table presents the regression results of market reaction tests. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

5. Additional analyses and robustness tests

5.1 Endogeneity tests

Like other empirical studies, one potential concern regarding my baseline model is endogeneity resulting from correlated omitted variables. My estimates may be biased if there are correlated omitted variables that influence both climate disasters and analyst forecast properties simultaneously. It is also plausible that the measurement errors of my key variable may lead to biased estimates. To address these endogeneity concerns, I, therefore, employ two approaches. First, I adopt a 2SLS approach. Following prior literature (Albouy et al., 2016; Huang et al., 2018), I use population density, defined as the ratio of the annual population at the state level and the land area, as an instrumental variable for climate disasters. I obtain both state-level population and land area data from the U.S. Census Bureau. In my context, population density is correlated with climate disasters, thus satisfying the relevance condition. In addition, a thorough literature search indicates that there is no documented evidence on the relation between the instrument and firms' information environment. Put differently, it is unlikely that population density is associated with firms' information environment, satisfying the exclusion condition.

As shown in Table 8, I find that population density is negatively associated with climate disasters at the 1% level in the first stage regression (coef. =-0.001, t-stat. =-3.01), which is consistent with Huang et al. (2018). Furthermore, the Cragg-Donald F (*CDF*) statistic is 9.065, which is greater than the suggested cutoff value of 8.96 as identified in Stock and Yogo (2005), satisfying the relevance criteria of the instrument. In the second stage, I find that the coefficients on climate disasters are positive and statistically significant for both *AFE* (coef. =1.314, t-stat. =4.73) and *DISP* (coef. =0.006, t-stat. =3.84) at the 1% level, respectively. Therefore, the 2SLS regression results indicate that my baseline results are not biased, lending further support to my main findings.

Second, to further mitigate the correlated omitted variable concern, I include firm-level rather than industry-level fixed effects to control for unobservable time-invariant firm-level characteristics. In addition, I also include analyst level fixed effects to control for unobservable time-invariant analyst-level characteristics. The results reported in the last four columns of Table 8 show that the coefficients are significant at the 1% level,[15] suggesting that my baseline results continue to hold when controlling for either firm- or analyst- level fixed effects.

Table 8: Relation between climate disasters and firms' information environment: Endogeneity tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AFE		DISP		AFE	DISP	AFE	DISP
	1st stage	2nd stage	1st stage	2nd stage				
CDP		**1.314*** (4.73)**		**0.006*** (3.84)**	**0.004* (1.89)**	**0.011*** (4.54)**	**0.006*** (4.08)**	**0.012*** (5.89)**
Density	-0.001*** (-3.01)		-0.001*** (-3.01)					
Size	-0.035*** (-8.36)	0.148*** (12.76)	-0.035*** (-8.36)	0.001*** (14.84)	0.000 (1.14)	0.000 (0.85)	0.001*** (7.90)	0.001*** (5.32)
Loss	0.076*** (5.19)	1.013*** (30.09)	0.076*** (5.19)	0.011*** (53.10)	0.009*** (7.79)	0.009*** (8.90)	0.011*** (8.56)	0.011*** (10.00)
ROA	0.185*** (3.68)	-1.574*** (-15.84)	0.185*** (3.68)	-0.019*** (-29.10)	-0.018*** (-3.92)	-0.023*** (-5.45)	-0.014*** (-4.41)	-0.019*** (-6.20)
MTB	-0.008*** (-10.78)	-0.003 (-1.35)	-0.008*** (-10.78)	-0.000*** (-8.19)	-0.000*** (-3.50)	-0.000*** (-5.20)	-0.000*** (-4.87)	-0.000*** (-4.84)
Sgrowth	0.357*** (24.70)	-0.622*** (-6.01)	0.357*** (24.70)	-0.005*** (-8.24)	-0.001*** (-3.06)	-0.002*** (-4.84)	-0.002*** (-3.16)	-0.003*** (-5.58)
Age	0.002*** (8.19)	-0.004*** (-5.54)	0.002*** (8.19)	-0.000*** (-4.58)	-0.000 (-0.69)	-0.000 (-1.27)	-0.000 (-1.47)	0.000 (0.16)
SDret	0.445 (1.64)	23.255*** (44.46)	0.445 (1.64)	0.250*** (63.48)	0.194*** (11.35)	0.205*** (11.72)	0.235*** (12.85)	0.249*** (13.20)
Horizon	0.001*** (5.09)	0.003*** (30.53)	0.001*** (5.09)	0.000*** (9.47)	0.000*** (22.23)	0.000*** (7.15)	0.000*** (16.95)	0.000*** (12.20)
NOA	0.017*** (9.24)	-0.030*** (-17.55)	0.017*** (9.24)	-0.000*** (-18.13)	-0.000*** (-5.29)	-0.000 (-0.37)	-0.000*** (-9.39)	-0.000*** (-8.52)
NOC	0.000 (0.11)	-0.001 (-0.75)	0.000 (0.11)	-0.000 (-0.09)	-0.000 (-1.09)	-0.000 (-1.09)	-0.000 (-1.18)	-0.000** (-2.46)
NOF	0.001 (0.64)	0.010*** (3.49)	0.001 (0.64)	0.000*** (21.22)	0.000 (0.38)	0.000*** (8.52)	0.000*** (3.56)	0.000*** (10.87)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Firm	No	No	No	No	Yes	Yes	No	No
Analyst	No	No	No	No	No	No	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

[15] With the exception of Model 5, where the coefficient on *CDP* is marginally significant at the 10% level.

State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	382,321	382,321	382,321	382,203	382283	382265	380890	380873
R^2	0.204		0.204		0.4017	0.5214	0.2841	0.3514
CDF	9.065		9.065					

This table reports the regression results for endogeneity tests. The first four columns report the results based on the instrument variable approach while the last four columns control for either firm- or analyst- level fixed effects. The dependent variable in the first stage regression is climate disasters (*CDP*). The instrumental variable is population density. *CDF* represents *Cragg-Donald F statistic*. All other variables are defined in the appendix. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

5.2 Robustness tests

5.2.1 A difference-in-differences analysis

To bolster a potential causal inference between climate disasters and firms' information environment, I further investigate how a firms' information environment changes in response to a climate disaster event using a difference-in-differences model. Using hurricanes as exogenous shocks has been substantiated in the existing literature (e.g., Bourveau and Law, 2021; Dessaint and Matray, 2017), because the occurrence of hurricanes is largely not affected by firms' behaviors. Following this stream of literature, I focus on the Superstorm Sandy and investigate how it affects firms' information environment. I choose Superstorm Sandy because it caused most devastating damages in terms of employment (22.08 percent vs. 9.21 percent of Hurricane Katrina in 2005) to the U.S. economy and has been identified as one of the largest storms in the U.S. history.

I define a firm as affected if its headquarter is located within the state hit by Superstorm Sandy in 2012, otherwise I treat the firm as unaffected. The year of disaster, 2012, is excluded from the analysis. I follow prior literature (e.g., Bourveau and Law, 2021) to choose the length of the event window. Given I employ the arrival of Hurricane Sandy, the second costliest hurricane in U.S. history, I first restrict my analysis to three years before and three years after the disaster to mitigate the concern about the potential effects of confounding events. I further delete the year of 2009 to mitigate the influence of financial crisis. I compare the information environment of affected and unaffected firms before and after the Superstorm Sandy using the following difference-in-differences (DiD) specification:

$$FIE_{it} = \alpha_1 Affected_{it} + \alpha_2 Post_{it} + \alpha_3 Affected_{it} * Post_{it} + \sum X_{it} + \gamma_i + \delta_t + \theta_k + \varepsilon_{it} \quad (3)$$

where i,t,k denotes firms, years, and analysts, respectively. Control variables are the same as defined in the baseline model. *Affected* is a dummy variable taking the value of one if a firm's headquarter is located in the state hit by Superstorm Sandy, zero otherwise. *Post* is a dummy variable that takes the value of one for the years 2013-2015, and zero for the years 2010-2011. γ_i, δ_t, θ_k are firm-, year-, and analyst-level fixed effects. My variable of interest is the interaction between *Affected* and *Post*. If Superstorm Sandy worsens firms' information environment, the coefficient on the interaction term (α_3) is expected to be positive.

Table 9 reports the results for the DiD analysis. The coefficients on *Post* and *Affected* are suppressed due to the introduction of firm-, year-, and analyst-level fixed effects. As shown in Table 9, the coefficients on the interaction term in both models are statistically significant at the 5% significance level (coef. =0.002, t-stat.= 2.59 and coef. =0.002, t-stat.= 3.03), which further corroborates my baseline findings as well as lend support to a causal interpretation between climate disasters and firms' information environment.

Table 9: Relation between climate disasters and firms' information environment: A DiD analysis

	(1) AFE	(2) DISP
Affected*Post	**0.002**** **(2.59)**	**0.002***** **(3.03)**
Size	-0.001 (-0.53)	-0.001 (-0.79)
Loss	0.008*** (5.16)	0.007*** (5.93)
ROA	-0.018 (-1.08)	-0.019 (-1.42)
MTB	-0.000 (-0.80)	-0.000* (-2.01)
Sgrowth	-0.001 (-0.49)	-0.000 (-0.09)

Age	-0.001***	-0.002***
	(-3.84)	(-5.13)
SDret	0.140***	0.149***
	(4.92)	(6.61)
Horizon	0.000***	0.000***
	(3.25)	(4.11)
NOA	-0.000	0.000
	(-0.48)	(0.97)
NOC	0.000	-0.000
	(1.10)	(-0.89)
NOF	0.000*	0.000**
	(1.91)	(2.23)
Constant	0.042***	0.052***
	(2.97)	(4.18)
Firm	Yes	Yes
Year	Yes	Yes
Analyst	Yes	Yes
N	8253	8249
R^2	0.7448	0.7412

This table presents the regression results of the relation between climate disasters and firms' information environment using the DiD analysis. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

My DiD results are based on an important underlying assumption of parallel trends, which states that firms in both treated and control groups should have similar information environment before experiencing Superstorm Sandy. To validate this important assumption, I generate a set of indicator variables *D(t=i)* including *D(t=-2), D(t=-1), D(t=1), D(t=2), D(t=3)* and interact them with the *Affected* variable. Table 10 reports the verification of the parallel trends assumption.

As can be seen from Table 10, I find that the coefficient on the interaction term *D(t=-1)*Affected* is insignificant at the conventional level, suggesting that there is no significant trending difference in firms' information environment between treated and control firms before the hurricane.[16] However, the differences appear after the occurrence of Hurricane Sandy, as reflected in the significant coefficients on *D(t=1)*Affected*, *D(t=2)*Affected*, and *D(t=3)*Affected*.

[16] *D(t=-2)*Affected* is automatically dropped in the regression due to multicollinearity.

However, the effect starts to decay after two years, as indicated by the magnitude and significance of the coefficient on *D(t=3)*Affected*.

Table 10: Parallel trends assumption

	(1) AFE	(2) DISP
D(t=-2)*Affected	0.000	0.000
	(.)	(.)
D(t=-1)*Affected	0.001	0.001
	(1.18)	(0.88)
D(t=1)*Affected	0.002*	0.003***
	(1.73)	(3.50)
D(t=2)*Affected	0.004***	0.003***
	(3.79)	(3.76)
D(t=3)*Affected	0.003*	0.002
	(1.94)	(1.30)
Size	-0.001	-0.001
	(-0.52)	(-0.76)
Loss	0.008***	0.007***
	(5.12)	(5.94)
ROA	-0.019	-0.019
	(-1.09)	(-1.44)
MTB	-0.000	-0.000**
	(-0.81)	(-2.01)
Sgrowth	-0.001	-0.000
	(-0.50)	(-0.09)
Age	-0.001***	-0.002***
	(-3.90)	(-5.10)
SDret	0.140***	0.149***
	(4.87)	(6.55)
Horizon	0.000***	0.000***
	(3.24)	(4.08)
NOA	-0.000	0.000
	(-0.45)	(0.93)
NOC	0.000	-0.000
	(1.11)	(-0.88)
NOF	0.000*	0.000**
	(1.89)	(2.21)
Constant	0.042***	0.051***
	(2.97)	(4.13)
Firm	Yes	Yes
Year	Yes	Yes

Analyst	Yes	Yes
N	8253	8249
R2	0.7451	0.7413

This table presents the regression results of the verification of the parallel trends assumption. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

5.2.2 Alternative measures for firms' information environment

Prior literature has measured firms' information environment using trading volume and bid-ask spread (e.g., Harford et al., 2019). I follow the literature and use both measures as alternative proxies for firms' information environment. A firm's bid-ask spread (*Spread*) is calculated as the ratio of the difference between the bid and ask prices scaled by the average of bid and ask prices at the forecast date. A higher bid-ask spread implies an inferior information environment and vice versa. A firm's trading volume (*Volume*) increases when it has less information asymmetry. Thus, trading volume is positively related to a firm's information environment. A detailed definition of trading volume and bid-ask spread can be found in the Appendix.

Table 11 reports the results from the regressions using alternative measures. As shown in Columns (1) and (2) of Table 11, I find that climate disasters are negatively and significantly associated with trading volume (coef. =-0.470, t-stat. =-20.90), while they are positively and significantly associated with bid-ask spread (coef. =2.733, t-stat. =5.36), implying that my baseline findings are robust to using these alternative measures of firms' information environment.

5.2.3 Alternative measures for climate disasters

In my main analysis, climate disasters are proxied by the total property damages caused by climate disasters. In this subsection, I use several alternative measures for climate disasters to re-examine the relation between climate disasters and firms' information environment. First, I generate a rank score based on the amount of total monetary damages incurred each year. To this end, I first sort and rank state-level weather-related damages by year from 1 to 52 and re-scale using the formula *CDP* rank (hereafter *CDPR*) = (53-rank)/52 to make sure that the transformed ranking score is within the range from 0 and 1.[17] Consistent with the non-transformed index, a higher CDPR score indicates greater risk and vice versa.

Second, considering that some industries such as agriculture and food industries are more susceptible to climate-related disasters than others, I therefore follow Miao et al. (2018) and use the sum of total property and crop damages as a second alternative proxy for climate disasters. I use *CDPT* to represent the total damages resulting from climate catastrophe events. In addition, the same set of explanatory variables as employed in the baseline regression is used.

Turning to Columns (3) through (6), I find and document that *CDPT* and *CDPR* are positively associated with both analyst forecast errors and dispersion across all specifications, further bolstering my baseline results. Overall, the findings demonstrate that the negative relation between climate disaster risk and firms' information environment is unchanged for all these alternative measures.

Finally, I replicate my regression using the county-level total property disaster damages (*CDPC*). As mentioned earlier, a major caveat of this measure is that the total disasters damages are averaged out across all counties in the disaster-stricken states even if some counties are not directly hit by the disaster. As shown in the last two columns of Table 11, I find that *CDPC* is significantly positively associated with both analyst forecast errors and dispersion (coef. =0.001, t-stat.= 3.61 and coef. =0.001, t-stat.= 6.46) at the 1% level, further confirming my main findings.

Table 11: Relation between climate disasters and firms' information environment: Alternative measures

	(1) Volume	(2) Spread	(3) AFE	(4) DISP	(5) AFE	(6) DISP	(7) AFE	(8) DISP
CDP	**-0.470***** **(-20.90)**	**2.733***** **(5.36)**						
CDPT			**0.001***** **(4.80)**	**0.009***** **(7.41)**				

[17] The economic losses data for U.S. territories such as Puerto Rico is only available from 2010-2018. The CDP rank is calculated as (CDPR) = (52-rank)/51 for the period prior to 2010.

CDPR					**3.220** **(2.47)**	**0.321** **(2.27)**		
CDPC							**0.001***** **(3.61)**	**0.001***** **(6.46)**
Size	0.169*** (106.17)	-1.299*** (-83.06)	0.001*** (6.41)	0.103*** (8.20)	0.103*** (8.22)	0.001*** (6.34)	0.001*** (8.34)	0.001*** (6.45)
Loss	0.014*** (5.76)	1.188*** (12.19)	0.011*** (9.45)	1.113*** (8.17)	1.113*** (8.18)	0.011*** (9.47)	0.011*** (8.25)	0.011*** (9.55)
ROA	0.115*** (13.26)	-5.538*** (-14.73)	-0.018*** (-6.67)	-1.336*** (-4.95)	-1.334*** (-4.94)	-0.018*** (-6.70)	-0.013*** (-5.02)	-0.018*** (-6.75)
MTB	0.010*** (46.08)	-0.071*** (-23.77)	-0.000*** (-4.55)	-0.014*** (-4.69)	-0.014*** (-4.73)	-0.000*** (-4.62)	-0.000*** (-4.71)	-0.000*** (-4.57)
Sgrowth	0.125*** (37.22)	-1.493*** (-15.58)	-0.003*** (-5.54)	-0.155*** (-2.91)	-0.151*** (-2.79)	-0.003*** (-5.34)	-0.002*** (-2.87)	-0.003*** (-5.57)
Age	-0.003*** (-38.56)	0.012*** (11.42)	-0.000 (-0.80)	-0.001 (-1.52)	-0.001 (-1.51)	-0.000 (-0.77)	-0.000 (-1.52)	-0.000 (-0.79)
SDret	2.661*** (45.11)	63.734*** (22.82)	0.253*** (13.00)	23.837*** (12.42)	23.843*** (12.48)	0.253*** (13.06)	0.238*** (12.53)	0.253*** (13.07)
Horizon			0.000*** (11.22)	0.004*** (17.65)	0.004*** (17.67)	0.000*** (11.46)	0.000*** (17.89)	0.000*** (11.99)
NOA			-0.000*** (-9.18)	-0.023*** (-8.50)	-0.023*** (-8.52)	-0.000*** (-9.16)	-0.000*** (-8.56)	-0.000*** (-9.32)
NOC			-0.000 (-0.02)	-0.001 (-0.60)	-0.001 (-0.60)	-0.000 (-0.02)	-0.000 (-0.89)	-0.000 (-0.05)
NOF			0.000*** (9.38)	0.012** (2.16)	0.012** (2.15)	0.000*** (9.35)	0.000** (2.22)	0.000*** (9.96)
Constant	-1.203*** (-104.52)	13.515*** (86.06)	-0.005*** (-4.46)	-0.814*** (-6.72)	-0.846*** (-6.74)	-0.006*** (-4.63)	-0.008*** (-6.86)	-0.005*** (-4.43)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	No	No	Yes	Yes	Yes	Yes	Yes	Yes
N	382321	380643	382303	382321	382321	382303	382321	382303
R^2	0.2069	0.2010	0.3006	0.2272	0.2272	0.3002	0.2271	0.3004

This table presents the regression results of the relation between climate disasters and firms' information environment, using two alternative measures for firms' information environment and three alternative measures for climate disasters, respectively. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

5.2.4 Additional analysis

One potential concern related to my study is that my findings may be driven by observations during the financial crisis periods (Loh and Stulz, 2018). Analysts face more performance challenges during these periods since the financial crisis fundamentally complicated their forecasting tasks. To address this concern, I conduct a subsample analysis by excluding observations during the financial crisis periods of 2007-2009. Columns (1) and (2) of Table 12 report the results for the non-financial crisis periods. I find that, as expected, there is still a negative relation between climate disasters and firms' information environment during the non-financial crisis periods, consistent with my main findings.

Another concern in my study is that my results may be driven by firms in high-climate-disaster years. Bourveau and Law (2021) demonstrate a negative association between Hurricane Katrina and analyst performance. It is well known that monster hurricanes Katrina and Harvey struck the U.S. in 2005 and 2017, respectively, causing disproportionally significantly large damages in these two years, as already reflected in Figure 1. These two catastrophic events may significantly exacerbate the forecasting challenges. To alleviate this concern, I delete observations in years 2005 and 2017 and re-estimate the model. Results presented in Columns (3) and (4) of Table 12 suggest that my baseline findings are not driven by these two abnormal years.

Furthermore, Gulf Coast states, including Florida, Louisiana, Mississippi, and Texas, suffer significantly from weather-related disasters. As illustrated by the statistics listed in Table 2, these four states rank as the top four in terms of economic damages stemming from climate disasters. Therefore, it is plausible that my findings are driven by observations from firms located the Gulf Coast states. To address this concern, I exclude firms located in the Gulf Coast states and re-examine my findings. The results reported in Columns (5) and (6) of Table 12 suggest that my main findings continue to hold even when focusing on non-Gulf Coast states.

It is also plausible that some firms in the U.S. operate across states and even countries for various reasons such as tax purposes. Thus, all firms can be divided into either single-segment or multiple-segment firms based on different criteria. My main findings may be biased if I treat both types of firms equally because the place where a firm is headquartered may not coincidentally be the same place where its major plant operates. To mitigate this concern, I focus on Geographic and State Segment data (Compustat Segments Data) to distinguish single-segment firms from multiple-segment firms because my climate disaster risk measure is constructed at the state level. Of the 4,845 firms in my initial sample, I exclude 2,646 firms that are identified as multiple-segment firms. The results reported in the Columns (7) and (8) of Table 12 suggest that my main findings continue to hold when focusing on single-segment firms.

Table 12: Relation between climate disasters and firms' information environment: Additional robustness tests

	(1) Non-financial crisis period (AFE)	(2) Non-financial crisis period (DISP)	(3) Exclude high climate disaster Year (AFE)	(4) Exclude high climate disaster Year (DISP)	(5) Non-Gulf Coast (AFE)	(6) Non-Gulf Coast (DISP)	(7) Single-segment firms (AFE)	(8) Single-segment firms (DISP)
CDP	**0.612*** (5.07)**	**0.013*** (4.82)**	**0.962*** (3.23)**	**0.007*** (2.78)**	**1.205*** (4.18)**	**0.005* (1.90)**	**0.506*** (5.66)**	**0.008*** (9.22)**
Size	0.073*** (4.87)	0.001*** (4.75)	0.109*** (8.46)	0.001*** (6.07)	0.100*** (26.83)	0.001*** (27.83)	0.218*** (6.87)	0.002*** (7.19)
Loss	0.853*** (7.03)	0.009*** (8.79)	1.168*** (8.22)	0.012*** (9.93)	1.135*** (60.35)	0.011*** (75.41)	2.403*** (11.26)	0.022*** (14.28)
ROA	-1.633*** (-6.40)	-0.019*** (-7.48)	-1.276*** (-4.42)	-0.018*** (-6.43)	-1.109*** (-16.57)	-0.016*** (-28.79)	-0.808 (-0.83)	-0.008 (-1.10)
MTB	-0.013*** (-4.42)	-0.000*** (-4.20)	-0.016*** (-4.84)	-0.000*** (-4.32)	-0.015*** (-25.08)	-0.000*** (-34.03)	-0.014*** (-2.76)	-0.000*** (-2.90)
Sgrowth	-0.146*** (-3.19)	-0.003*** (-6.06)	-0.161*** (-3.03)	-0.003*** (-6.05)	-0.195*** (-11.17)	-0.003*** (-18.01)	0.062 (0.86)	-0.000 (-0.03)
Age	-0.002 (-1.51)	-0.000 (-0.89)	-0.001 (-1.41)	-0.000 (-0.52)	-0.000** (-1.98)	-0.000 (-0.11)	0.000 (0.03)	-0.000 (-0.36)
SDret	19.314*** (8.20)	0.226*** (7.76)	23.699*** (11.83)	0.251*** (12.83)	23.638*** (50.18)	0.244*** (60.16)	39.941*** (12.67)	0.377*** (10.93)
Horizon	0.003*** (15.27)	0.000*** (10.57)	0.004*** (17.36)	0.000*** (9.97)	0.004*** (68.46)	0.000*** (22.04)	0.005*** (13.30)	0.000*** (6.97)
NOA	-0.021*** (-7.23)	-0.000*** (-8.84)	-0.024*** (-8.20)	-0.000*** (-8.37)	-0.022*** (-46.77)	-0.000*** (-38.19)	-0.055*** (-11.29)	-0.000*** (-9.47)
NOC	-0.001 (-1.44)	-0.000 (-0.49)	-0.001 (-0.57)	-0.000 (-0.15)	-0.001 (-1.43)	-0.000 (-0.01)	0.003 (1.29)	0.000 (0.83)
NOF	0.009 (1.41)	0.000*** (8.88)	0.012** (2.11)	0.000*** (7.70)	0.017*** (10.79)	0.000*** (27.93)	0.019 (1.50)	0.000*** (6.43)
Constant	-0.423*** (-3.56)	-0.003** (-2.04)	-0.847*** (-6.67)	-0.005*** (-4.26)	-0.885*** (-26.96)	-0.006*** (-22.63)	-1.988*** (-7.33)	-0.014*** (-7.29)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	315318	315302	334257	334243	321369	321352	122626	122618
R^2	0.1992	0.2726	0.2321	0.3063	0.2302	0.3028	0.2431	0.3058

This table presents the additional regression results as robustness tests of the relation between climate disasters and firms' information environment. The t-statistics (reported in parentheses) are based on standard errors double clustered at the state and analyst levels. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Finally, I implement additional tests to further corroborate my baseline findings. First, prior literature has shown differential impacts of various natural disasters (e.g., Skidmore and Toya, 2002). Although geophysical disasters have been excluded from my analysis, I follow the prior literature and divide all climate disasters into two subcategories: “hurricane and tropical storms” and “non-hurricane and tropical storms disasters”. Second, I replace the main independent variable CDP, with its corresponding one-year lag variable. Third, unlike the main regression model where I cluster standard errors at the state and analyst level, as a robustness test I cluster standard errors at the analyst-, brokerage-, and state-level. Untabulated results suggest my baseline findings are qualitatively unchanged under these different specifications and subsamples. Overall, these findings highlight the robustness of my main findings.

6. Conclusion

Climate change has started to exert an increasingly significant impact on firms’ behaviors and outcomes. Recently more academic attention has been devoted to exploring the firm-level effects of natural disasters. I extend the literature by concentrating on the effects of climate disasters on firms’ information environment.

Using a large sample of 382,471 observations in the U.S. over 2001-2017, I document that climate disasters are negatively associated with firms’ information environment. The results from market reaction tests provide further support for my main findings. In additional tests, I find that the negative relation between climate disasters and firms’ information environment is more pronounced for firms in the climate-vulnerable industries and identify the volatility of ROA and cash flows as two possible channels through which climate disasters influence corporate information environment. My findings are robust to alternative measures of climate disasters and firms’ information environment, different model specifications, and different subsamples.

My study contributes to the literature in several important ways. First, I extend the micro-effect of climate risk studies by focusing on its effect on firms’ information environment. To the best of my knowledge, I am among the first to address this important issue. Understanding how and to what extent climate disasters are associated with firms' information environment has significant implications for market participants, firms, and regulators. Second, my study also adds to the literature focusing on the micro-level impact of uncertainty. Unlike this literature which extensively focuses on conventional uncertainties, such as economic policy uncertainty and political uncertainty, my study extends this line of literature by focusing on uncertainty arising from climate disasters. Although not the focus of my study, I also add to the analyst forecast literature by identifying a potential environmental exogenous determinant which is largely neglected in the prior literature.

My findings that climate disasters negatively associated with firms' information environment have significant implications for academics, standard setters, analysts, and investors. In particular, considering the recent move of SEC towards the rulemaking of climate risk disclosures, my results suggest that climate risk-related disclosures are a feasible means that can compensate the deteriorated corporate information environment caused by climate disasters. Under the context of climate change, investors who heavily rely on analysts to translate an overwhelming amount of information to meaningful implications may exercise caution based on my findings. They may also resort to other firm-level climate-related disclosures to compensate for the exacerbated information environment to make better financial decisions.

References:

Abarbanell, J. S. (1991). Do analysts' earnings forecasts incorporate information in prior stock price changes? *Journal of Accounting and Economics*, 14, 147-165.

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, 33(3), 1331-1366.

Albouy, D., Graf, W., Kellogg, R., & Wolff, H. (2016). Climate amenities, climate change, and American quality of life. *Journal of the Association of Environmental and Resource Economists*, 3(1), 205-246.

Amiram, D., Landsman, W. R., Owens, E. L., & Stubben, S. R. (2018). How are analysts' forecasts affected by high uncertainty? *Journal of Business Finance & Accounting*, 45(3-4), 295-318.

Beck, T., Levine, R., & Levkov, A. (2010). Big bad banks? The winners and losers from bank deregulation in the United States. *The Journal of Finance*, 65(5), 1637-1667.

Benson, C., & Clay, E. (2004). Understanding the economic and financial impacts of natural disasters. Disaster Risk Management Series No. 4. The World Bank, Washington, DC.

Bloom, N. (2014). Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2), 153-176.

Bourveau, T., & Law, K. K. (2021). Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes. *The Accounting Review*, 96(3), 121-140.

Bradshaw, M. T., Huang, A. G., & Tan, H. (2019). The effects of analyst‐country institutions on biased research: Evidence from target prices. *Journal of Accounting Research*, 57(1), 85-120.

CEMHS, 2018. Spatial Hazard Events and Losses Database for the United States, Version 17.0. [Online Database]. Phoenix, AZ: Center for Emergency Management and Homeland Security, Arizona State University

Chourou, L., Purda, L., & Saadi, S. (2021). Economic policy uncertainty and analysts' forecast characteristics. *Journal of Accounting and Public Policy*, 40(4), 106775.

Ciccone, S. (2003). Does analyst optimism about future earnings distort stock prices? *The Journal of Behavioral Finance*, 4(2), 59-64.

Clement, M. B., & Tse, S. Y. (2005). Financial analyst characteristics and herding behavior in forecasting. *The Journal of Finance*, 60(1), 307-341.

Cutter, S. L., & Emrich, C. (2005). Are natural hazards and disaster losses in the US increasing? EOS, *Transactions American Geophysical Union*, 86(41), 381-389.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3), 66-95.

Dichev, I. D., & Tang, V. W. (2009). Earnings volatility and earnings predictability. *Journal of Accounting and Economics*, 47(1-2), 160-181.

Diether, K. B., Malloy, C. J., & Scherbina, A. (2002). Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5), 2113-2141.

Ding, R., Liu, M., Wang, T., & Wu, Z. (2021). The impact of climate risk on earnings management: International evidence. *Journal of Accounting and Public Policy*, 40(2), 106818.

Duru, A., & Reeb, D. M. (2002). International diversification and analysts' forecast accuracy and bias. *The Accounting Review*, 77(2), 415-433.

Eckstein, D., Lena Hutfils, M., & Winges, M. (2019). Global climate risk index 2019. *Germanwatch, Bonn*.

Gall, M., Borden, K. A., & Cutter, S. L. (2009). When do losses count? Six fallacies of natural hazards loss data. *Bulletin of the American Meteorological Society*, 90(6), 799-810.

Gallagher, J., & Hartley, D. (2017). Household finance after a natural disaster: The case of Hurricane Katrina. *American Economic Journal: Economic Policy*, 9(3), 199-228.

Gerakos, J., & Kovrijnykh, A. (2013). Performance shocks and misreporting. *Journal of Accounting and Economics*, 56(1), 57-72.

Griffin, J. M., Kelly, P. J., & Nardari, F. (2010). Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. *The Review of Financial Studies*, 23(8), 3225-3277.

Groysberg, B., Healy, P. M., & Maber, D. A. (2011). What drives sell-side analyst compensation at high-status investment banks? *Journal of Accounting Research*, 49(4), 969-1000.

Hann, R. N., Ogneva, M., & Sapriza, H. (2012). Forecasting the macroeconomy: Analysts versus economists. Available at SSRN 2194179.

Harford, J., Jiang, F., Wang, R., & Xie, F. (2019). Analyst career concerns, effort allocation, and firms' information environment. *The Review of Financial Studies*, 32(6), 2179-2224.

Heal, G., & Millner, A. (2014). Reflections: Uncertainty and decision making in climate change economics. *Review of Environmental Economics and Policy*, 8(1), 120-137.

Healy, P. M., Hutton, A. P., & Palepu, K. G. (1999). Stock performance and intermediation changes surrounding sustained increases in disclosure. *Contemporary Accounting Research*, 16(3), 485-520.

Hodges, J., Leatherby, L., & Mehrota, K. (2018). Climate change warriors' latest weapon of choice is litigation. Bloomberg, May 24. https://www.bloomberg.com/graphics/2018-climate-change-lawsuits/

Hong, H., & Kubik, J. D. (2003). Analyzing the analysts: Career concerns and biased earnings forecasts. *The Journal of Finance*, 58(1), 313-351.

Hope, O. K. (2003). Disclosure practices, enforcement of accounting standards, and analysts' forecast accuracy: An international study. *Journal of Accounting Research*, 41(2), 235-272.

Hope, O. K., & Kang, T. (2005). The association between macroeconomic uncertainty and analysts' forecast accuracy. *Journal of International Accounting Research*, 4(1), 23-38.

Horton, J., Serafeim, G., & Serafeim, I. (2013). Does mandatory IFRS adoption improve the information environment? *Contemporary Accounting Research*, 30(1), 388-423.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., & Larsen, K. (2017). Estimating economic damage from climate change in the United States. *Science*, 356(6345), 1362-1369.

Hsu, P. H., Lee, H. H., Peng, S. C., & Yi, L. (2018). Natural disasters, technology diversity, and operating performance. *Review of Economics and Statistics*, 100(4), 619-630.

Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5), 633-656.

Hugon, A., & Muslu, V. (2010). Market demand for conservative analysts. *Journal of Accounting and Economics*, 50(1), 42-57.

Intergovernmental Panel on Climate Change (IPCC). (2008). Climate Change 2007: Synthesis Report. Geneva: Intergovernmental Panel on Climate Change.

Jackson, A. R. (2005). Trade generation, reputation, and sell-side analysts. *The Journal of Finance*, 60(2), 673-717.

Kahneman, D. (1973). *Attention and effort* (Vol. 1063). Englewood Cliffs, NJ: Prentice-Hall.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, 47(2), 263-291.

Keskek, S., & Tse, S. Y. (2018). Does forecast bias affect financial analysts’ market influence? *Journal of Accounting, Auditing & Finance*, 33(4), 601-623.

Kong, D., Lin, Z., Wang, Y., & Xiang, J. (2021). Natural disasters and analysts' earnings forecasts. *Journal of Corporate Finance*, 66, 101860.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3), 1067-1111.

Lang, M. H., & Lundholm, R. J. (1996). Corporate disclosure policy and analyst behavior. *The Accounting Review*, 71(4), 467-492.

Lang, M. H., Lins, K. V., & Miller, D. P. (2003). ADRs, analysts, and accuracy: Does cross listing in the United States improve a firm's information environment and increase market value? *Journal of Accounting Research*, 41(2), 317-345.

Lehavy, R., Li, F., & Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, 86(3), 1087-1115.

Leuz, C., & Wysocki, P. D. (2016). The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research. *Journal of Accounting Research*, 54(2), 525-622.

Li, T., & Zaiats, N. (2017). Information environment and earnings management of dual class firms around the world. *Journal of Banking & Finance*, 74, 1-23.

Lim, T. (2001). Rationality and analysts' forecast bias. *The Journal of Finance*, 56(1), 369-385.

Loh, R. K., & Stulz, R. M. (2018). Is sell-side research more valuable in bad times? *The Journal of Finance*, 73(3), 959-1013.

Mattei, M. M., & Platikanova, P. (2017). Do product market threats affect analyst forecast precision? *Review of Accounting Studies*, 22(4), 1628-1665.

Miao, Q., Hou, Y., & Abrigo, M. R. (2018). Measuring the financial shocks of natural disasters: A panel study of US states. *National Tax Journal*, 71(1), 11-44.

Nagar, V., Schoenfeld, J., & Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, 67(1), 36-57.

Noy, I. (2009). The macroeconomic consequences of disasters. *Journal of Development Economics*, 88(2), 221-231.

Plumlee, M. A. (2003). The effect of information complexity on analysts' use of that information. *The Accounting Review*, 78(1), 275-296.

Raddatz, C. (2006). Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics*, 1(84), 155-187.

Ramnath, S., Rock, S., & Shane, P. (2008). The financial analyst forecasting literature: A taxonomy with suggestions for further research. *International Journal of Forecasting*, 24(1), 34-75.

Rauch, E. (2012). "*Global Natural Catastrophe Update*." In *2011 Natural Catastrophe Year in Review*, edited by Carl Hedde, 27–43. Princeton, NJ: Munich Reinsurance America.

Richardson, V. J. (2000). Information asymmetry and earnings management: Some evidence. *Review of Quantitative Finance and Accounting*, 15(4), 325-347.

Scherbina, A. (2008). Suppressed negative information and future underperformance. *Review of Finance*, 12(3), 533-565.

SECURITIES AND EXCHANGE COMMISSION (SEC), 2021. Public Input Welcomed on Climate Change Disclosures. Available at: https://www.sec.gov/news/public-statement/lee-climate-change-disclosures.

Skidmore, M., & Toya, H. (2002). Do natural disasters promote long-run growth? *Economic Inquiry*, 40(4), 664-687.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in Linear IV regression. In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 80-108). Cambridge University Press.

Walther, B. R., & Willis, R. H. (2013). Do investor expectations affect sell-side analysts' forecast bias and forecast accuracy? *Review of Accounting Studies*, 18(1), 207-227.

Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics*, 58(3), 369-396.

Wilson, M., & Wu, Y. (2011). Do publicly signalled earnings management incentives affect analyst forecast accuracy? *Abacus*, 47(3), 315-342.

World Economic Forum (WEF) (2020). The Global Risks Report 2020 https://www.weforum.org/reports/the-global-risks-report-2020

Zhang, X. F. (2006). Information uncertainty and analyst forecast behavior. *Contemporary Accounting Research*, 23(2), 565-590.

Appendix: Definitions of variables

Variables	Definitions
Measures of firms' information environment	
AFE	Analyst forecast error, defined as the absolute difference between actual annual earnings and the most recent individual analyst forecast value before earnings announcement, which is multiplied by 100 and scaled by the stock price at the forecast date. Source: I/B/E/S.
DISP	The standard deviation of annual analyst forecast values for a given firm scaled by the stock price at the beginning of the year. Source: I/B/E/S.
Others:	
Volume	The trading volume in millions of U.S. dollars. Source: CRSP.
Spread	The difference between bid and ask prices divided by the average of bid and ask prices on the forecast date. Source: CRSP.
Measures of climate disasters	
CDP	Total annual state-wide property damages from all hazard types of climate disasters. Source: SHELDUS.
Others:	
CDPT	Total annual state-wide property and crop damages from all hazard types of climate disasters. Source: SHELDUS.
CDPR	The rank of the CDP. CDPR ranges from 0 to 1. A higher score indicates more climate disasters in the year, and vice versa. Source: SHELDUS.
CDPC	Total annual county-wide property damages from all hazard types of climate disasters. Source: SHELDUS.
Other variables	
Size	Natural logarithm of total Assets (AT). Source: Compustat.
Loss	An indicator variable equal to 1 if a firm's net income is negative, and 0 otherwise. Source: Compustat.
ROA	Return on assets. Net income scaled by total assets. Source: Compustat.
MTB	Market value of equity divided by book value of equity. Source: Compustat.
Sgrowth	Percentage change of Sales (SALE). Source: Compustat.
Age	Firm age, which is computed based on the number of years the firm appears in Compustat. Source: Compustat.
SDret	The standard deviation of stock returns over 30 days leading up to the forecast. Source: CRSP.
Sur	The difference between actual earnings and analyst mean consensus forecast value. Source: I/B/E/S.
Horizon	The time between analyst forecast reporting date and actual EPS announcement date. Source: I/B/E/S.
NOA	The number of analysts following a firm. Source: I/B/E/S.
NOC	The number of firms followed by an analyst in a year. Source: I/B/E/S.
NOF	The number of earnings forecasts issued by an analyst in a year. Source: I/B/E/S.
CAR [-1,1]	Cumulative abnormal return for a three-day event window centered on the earnings announcement date. Source: CRSP.
CF_SD	The volatility of cash flows, measured as the standard deviation of cash flow over the past four years.
ROA_SD	The volatility of ROA, measured as the standard deviation of ROA over the past four years.
Vulnerability	An indicator variable that equals 1 for Agriculture (Fama–French Industry Code 1), Business Services (Code 34), Communication (Code 32), Energy [Mines (code 28), Coal (Code 29), Oil (Code 30)], Food Products (Code 2), Health Care (Code 11), and Transportation (Code 40), and 0 otherwise. Source: Compustat.
Population	The annual population of each state. Source: U.S. Census Bureau.
Land	The land area of each state. Source: U.S. Census Bureau.
Density	Population density: number of people per square mile of land area. Source: U.S. Census Bureau.
Post	An indicator variable that equals one for years 2013-2015, and zero for years 2010-2011.
Affected	An indicator variable that equals one if a firm's headquarter is located in a state hit by Superstorm Sandy, and zero otherwise.

D(t=-2)	A dummy variable equal to one for year 2010, and zero otherwise.
D(t=-1)	A dummy variable equal to one for year 2011, and zero otherwise.
D(t=1)	A dummy variable equal to one for year 2013, and zero otherwise.
D(t=2)	A dummy variable equal to one for year 2014, and zero otherwise.
D(t=3)	A dummy variable equal to one for year 2015, and zero otherwise.

Chapter 2: Climate Change Social Norms and Corporate Cash Holdings

1. Introduction

Social norms play a critical role in shaping individuals' behaviors (Chen, Podolski, Rhee, and Veeraraghavan, 2014; Hilary and Hui, 2009; McGuire, Omer, and Sharp, 2012; Young, 2021). Prior literature has documented various effects of climate change social norms (CCSN, hereafter) at both individual and firm levels (Allcott, 2011; Cialdini and Jacobson, 2021; Mase, Gramig, and Prokopy, 2017). Given the heightened level of climate change risk perception and belief after a series of climate-induced extreme weather events in the U.S. (Goldberg, Gustafson, Rosenthal, Kotcher, Maibach, and Leiserowitz, 2020), surprisingly, there is a dearth of research examining CCSN and its effects on corporate behaviors.

The purpose of the present study is to examine the influence of CCSN on corporate cash holdings.[18] Understanding the influence of CCSN on corporate cash holdings, one of the most important decisions made by the management, is important because cash accounts for roughly one-fifth of the total corporate assets[19] and can lead to substantial consequences (Bates et al., 2009; Frésard, 2010). Prior research exploring the determinants of corporate cash holdings focuses primarily on firm fundamentals and corporate governance attributes (e.g., Almeida, Campello, and Weisbach, 2004; Harford, Mansi, and Maxwell, 2008). Although the effects of different types of social norms on corporate decisions have been documented in the literature (e.g., Callen and Fang,

[18] There is no universally agreed definition on CCSN. I adopt and extend the definition used by Cialdini and Jacobson (2021) and define CCSN as the predominant behaviors, attitudes, beliefs, and codes of conduct of a group in response to climate change.

[19] Consistent with prior literature (e.g., Bates, Kahle, and Stulz, 2009), cash accounts for roughly 26% of the total corporate assets in my sample.

2015; Chen et al., 2014; Hilary and Hui, 2009), there is limited understanding of whether CCSN, a nascent of social norms, influences corporate cash holdings. I, therefore, aim to advance the literature on both social norms and corporate cash holdings by examining the influence of CCSN on corporate cash holdings.

I posit that CCSN positively relates to corporate cash holdings. Corporate finance theory offers several potential reasons why CCSN may have a positive influence on corporate cash policies. The first reason involves the firm's transaction motive. Managers of firms located in counties with higher CCSN may avoid future transaction costs resulting from climate-induced extreme weather events by accumulating more cash. Another reason is related to the precautionary motive. To address financing concerns in the aftermath of disasters, managers of firms in counties with higher CCSN are more likely to increase cash holdings. As noted by Jensen (1986), a third reason is that climate change events may exacerbate information asymmetry (Han, Mao, Tan, and Zhang, 2020), which gives managers a stronger incentive to accumulate cash to engage in cash appropriation at the expense of shareholders.

Alternatively, it is also plausible that CCSN is unrelated to cash holdings. Given that extreme weather events can exacerbate firms' information environment (Han et al., 2020) and widen the information gap between management and outside shareholders. Faced with increased corporate opacity, shareholders domiciled in counties with higher CCSN are more likely to take actions to deter managers' opportunistic behaviors by requiring managers to disgorge excess cash in the form of dividend payouts or share repurchases. In addition, as suggested by prior literature (e.g., Neef, Benge, Boruff, Pauli, Weber, and Varea, 2018), CCSN could induce managers of firms located in higher CCSN counties to foster climate resilience by engaging actively in environmental risk management. Further, Barreca, Clay, Deschenes, Greenstone, and Shapiro (2015, 2016) document that investments in technological and public health innovations can significantly reduce the negative impact of climate-induced extreme weather events. Therefore, the firm's operations as well as cash flows, are less likely to be adversely affected by disasters, mitigating its need to hold excess cash. Given these reasons, whether CCSN is positively associated with corporate cash holdings is ultimately an empirical research question.

I examine the relationship between CCSN and corporate cash holdings by constructing a county-level measure of CCSN using U.S. climate change opinion data from Yale Climate Opinion Maps (YCOM) over the period 2014-2020. My findings show that CCSN is significantly positively associated with corporate cash holdings, even after controlling for various known determinants of cash holdings identified in prior research. My results are both statistically and economically meaningful. Specifically, a one standard deviation increase in CCSN is associated with a 17.5% increase in cash holdings, highlighting the significant role of CCSN in influencing corporate cash policies.

I then proceed to address endogeneity concerns related to my main findings. I argue that reverse causality is unlikely in my research context because it is not possible that cash holdings shape CCSN at the community level. My findings, however, could be subject to omitted variable bias because unobserved regional characteristics could influence both CCSN and cash holdings simultaneously or be biased if there are measurement errors in my key variable of interest.

I address these endogeneity concerns in serval different ways. First, I employ a difference-in-differences (DiD, hereafter) specification by exploiting the occurrence of Hurricanes Harvey and Irma in 2017 as a plausibly exogenous shock to individuals' propensity to act on climate change. Second, I adopt an instrumental variable (IV) approach using three IVs: the percentage of individuals in a ZIP code voting for a particular political party, the implementation of Climate

Action Plans (CAPs), and the average county-level CCSN within a state. Third, I use changes-on-changes specifications to eliminate potential time-invariant omitted correlated variables. Fourth, I conduct an extensive array of subsample analyses based on geography and time periods. Fifth, I control for a group of additional demographic and political variables. Sixth, I employ alternative measures of CCSN. Finally, I perform additional robustness checks (e.g., state-level CCSN, industry×year fixed effects). My main findings continue to hold in all these tests.

Having established a positive association between CCSN and corporate cash holdings, I next implement several cross-sectional analyses to examine how financial constraints, media coverage of climate uncertainty, and climate risk exposure moderate the association between CCSN and cash holdings. Consistent with expectations, my evidence shows that the positive association between CCSN and corporate cash holdings is more pronounced for financially constrained firms, during years with a heightened level of media coverage of climate uncertainty, and for firms with greater climate risk exposures.

In further analyses, I consider several possible sources of cash flows and test whether CCSN influences the amount of dividend payouts, the likelihood of paying dividends, net working capital, capital expenditures, sales growth, stock repurchases, and new financing. I find that firms located in counties with higher CCSN reduce dividend payouts, are less likely to pay dividends, and curtail both net working capital and capital expenditures. However, I find no evidence that CCSN is related to sales growth, stock repurchases, and new financing.

Finally, I implement several additional tests to rule out alternative explanations for the positive association between CCSN and cash holdings. I find that my results are not driven by the presence of either R&D-intensive firms or “old-economy” manufacturing firms. In particular, my main findings cannot be reasonably explained by both tax and agency motives, further confirming my social-norms-based explanation.

My study contributes to the literature in several important ways. First, it documents a strong positive relationship between county-level CCSN and corporate cash holdings. In doing so, I add to the literature on determinants of cash holdings by documenting CCSN as a potential determinant. In particular, I provide a social-norms-based explanation associated with climate risk for the increased cash holdings in U.S. firms. Second, I expand the literature on the influence of CCSN by investigating its influence on corporate behaviors. Prior literature examining the effects of climate-related social norms typically focuses either at a macro level or at an individual level (e.g., Allcott, 2011; Mase et al., 2017). In contrast, I document some firm-level evidence that CCSN leads to a rise in corporate cash holdings. Third, I add to the literature on the effects of social norms on economic behaviors (e.g., Callen and Fang, 2015; Chen et al., 2014; Hilary and Hui, 2009; Kumar, Page, and Spalt, 2011), and particularly its impact on corporate cash holdings (Hu, Lian, and Zhou, 2019). However, prior studies in finance primarily focus on the effects of social norms related to either religion or gambling attitudes. To the best of my knowledge, this study is the first to empirically examine the influence of CCSN on cash holdings. Fourth, my study broadly contributes to the behavioral finance literature emphasizing the role of heuristics in the economic decision-making process against the backdrop of climate change (Dessaint and Matray, 2017). Given that past disaster experience alone cannot determine subsequent corporate behaviors (e.g., Howe, Mildenberger, Marlon, and Leiserowitz, 2015; O’Connor, Bard, and Fisher, 1999), I complement this literature by showing that CCSN, a nascent form of social norms, plays an important role in influencing corporate cash holdings.

The remainder of my study is structured as follows. Section two presents the relevant prior research and develops a testable hypothesis. Section three discusses the sample and research design. Section four discusses the empirical findings, and Section five concludes.

2. Related Literature and Hypothesis Development

2.1 Determinants of Corporate Cash Holdings

Considerable attention has been paid to the significant increase in cash holdings of U.S. firms in the literature (e.g., Bates et al., 2009). Existing literature has proposed four non-mutually exclusive theories (i.e., the transaction cost motive, the precautionary motive, the agency motive, and the tax motive) to explain firms' cash holding policies. Starting at least from Baumol (1952), there is a large but growing literature exploring determinants of corporate cash holdings based on these theories (e.g., Bates et al., 2009; Faulkender, Hankins, and Petersen, 2019; Harford, Klasa, and Maxwell, 2014; Jensen, 1986; Tobin, 1956). Earlier research focuses mostly on cash holdings' transaction and precautionary motives (e.g., Bates et al., 2009; Baumol, 1952; Opler et al., 1999; Tobin, 1956). Opler et al. (1999) find that cash holdings are determined by the tradeoff of costs and benefits of the holding of cash. Bates et al. (2009) examine the impact of both precautionary and agency motives on cash holdings. Specifically, they find that the precautionary motive explains the rise in cash holdings while agency theory fails to produce consistent results. More recently, Harford et al. (2014) also highlight the role of the precautionary demand for cash and identify refinancing risk as a possible determinant of corporate cash holdings. Pinkowitz et al. (2016) find that R&D investment drives corporate cash holdings. Without R&D-intensive firms in the U.S., on average, there are no differences in cash holdings between U.S. firms and foreign firms.

Existing literature also examines the determinants of cash holdings utilizing other theories. For example, based on agency theory, Jensen (1986) argues that managers have an incentive to hold more cash because they can invest in value-decreasing projects to reap personal gains at the expense of shareholders. Departing from Bates et al. (2009), Faulkender et al. (2019) further differentiate the precautionary motive from the tax motive. Their findings suggest that the precautionary motive applies principally to domestic cash holdings while the tax motive is the root of changes in cash holdings of foreign sub-branches of multinational companies.

2.2 Climate Change Social Norms

According to Cialdini and Jacobson (2021), social norms are "the predominant behaviors, attitudes, beliefs, and codes of conduct of a group". Anecdotal evidence and prior research suggest that corporate behaviors are likely to broadly reflect the social norms of the region where the firm is headquartered (Cialdini, Reno, and Kallgren, 1990; Kumar et al., 2011). Following this literature (e.g., Cialdini et al., 1990; Cialdini and Jacobson, 2021), I define CCSN as the predominant behaviors, attitudes, beliefs, and codes of conduct of a group in response to climate change.

Existing research has found that public perception of climate change can facilitate mitigation and adaptation policies (Howe et al., 2015; Lorenzoni and Pidgeon, 2006). Given its critical role, there is an extensive but growing literature documenting the determinants and consequences of CCSN (e.g., Howe et al., 2015; Lee, Markowitz, Howe, Ko, and Leiserowitz, 2015; Mase et al., 2017; Spartz, Su, Griffin, Brossard, and Dunwoody, 2017). For instance, Howe et al. (2015) find that Americans believing climate change range from 43% to 80% at the county level, depending on education, political ideology, and demographics. Turning to consequences arising from CCSN, there is mixed evidence. For example, Mase et al. (2017) find that CCSN induces Midwestern U.S. farmers to take adaptation measures against climate risk. In contrast, Harries (2012) suggests that CCSN may be dominated by feelings of anxiety and insecurity, leading to hindrance rather than the promotion of climate mitigation efforts.

In summary, although there is well-established literature on corporate cash holdings and nascent literature on CCSN, little research has been done to explore the influence of CCSN on corporate cash holdings. I, therefore, aim to bridge these two strands of literature and investigate this important issue.

2.3 Hypothesis Development

Drawing on the transaction and precautionary motives theories, I reason that firms headquartered in counties with higher CCSN are more likely to hold cash for two main reasons. First, Opler et al. (1999) suggest that cash holdings can reduce firm risk and increase managers' discretion. Extending this reasoning to a climate change setting, managers of firms located in higher CCSN counties are more likely to have a stronger incentive to hold cash. This is because it helps reduce financing risk arising from climate-induced extreme weather events and increase management discretion in the post-disaster periods, especially considering that climate risk is negatively associated with firms' return on assets (ROA) while positively associated with firms' cash flow volatility (Huang, Kerstein, and Wang, 2018). From the perspective of Keynes' (1936) transaction motive, sufficient cash holdings can avoid converting real assets into cash when it is needed. In addition, given that climate change brings about risks and opportunities, managers need not liquidate assets or raise funds through the capital market to invest when profitable investment opportunities arise (Shleifer and Vishny, 1992). Instead, they can use the liquid assets to finance, especially when the financing costs are expensive.

Second, my prediction that managers of firms in higher CCSN counties tend to hold more cash is also informed by the precautionary motive (Almeida et al., 2004; Denis and Sibilkov, 2010; Holmström and Tirole, 1998). According to the precautionary motive, financial constraints induce firms to manage liquidity assets (Holmström and Tirole, 1998). For example, Harford et al. (2014) find that firms reduce refinancing risk by accumulating cash for precautionary purposes. Under the climate change context, Berg and Schrader (2012) suggest that although demands for financing increase, firms have little access to financing in the post-disaster periods. From the perspective of precautionary motive, CCSN motivates managers to hold sufficient cash to relieve financing frictions in the aftermath of disasters. Otherwise, they may have difficulty keeping operating or have to cut back profitable investments due to cash shortfall. Consistent with this view, Opler et al. (1999) suggest that firms with profitable investment opportunities are more likely to hold cash to avoid a larger marginal cost arising from a shortage of funds. In a similar vein, Duchin, Ozbas, and Sensoy (2010) and Derrien and Kecskes (2013) find that firms holding more cash are less likely to be adversely affected by the rising cost of capital. Overall, the above arguments lead to the following hypothesis:

H1: Climate change social norms is positively related to corporate cash holdings.

Alternatively, firms in higher CCSN counties may not increase their cash holdings for the following reasons. To begin with, given that extreme weather events can exacerbate firms' information environment (Han et al., 2020) and widen the information gap between the management and shareholders, managers have a stronger incentive to appropriate cash and engage in other self-serving behaviors such as investing negative net present value (NPV) projects (Frésard and Salva, 2010). Faced with a heightened level of corporate opacity and a rising likelihood of managerial opportunism, shareholders from counties with higher CCSN are more likely to take preventive actions to deter managers' opportunistic behaviors by requiring managers to disgorge excess cash in the form of dividend payouts or share repurchases. Consequently, managers of firms located in higher CCSN counties are more likely to face pressure to disgorge cash. Furthermore, managers of firms located in counties with higher CCSN are more likely to strengthen climate resilience to cope with climate risk (Neef et al., 2018) by actively engaging in environmental risk management. As noted by Sharfman and Fernando (2008), improved environmental risk management is negatively associated with the firm's cost of capital because it changes public perception of the firm's risk profile. Further, Barreca et al. (2015, 2016) find that individuals increase capital investment beforehand to mitigate potential climate physical damage. Taken together, these firms' operations, as well as future cash flows, are less likely to be negatively affected by climate-induced extreme weather events, mitigating their need to hold excess cash. These arguments lead to some tension by suggesting a non-positive link between CCSN and cash holdings. Therefore, whether CCSN is positively associated with cash holdings is ultimately an empirical question.

3. Research Design

3.1 Data Source and Sample Selection

I obtain climate change opinion data from YCOM, financial data from Compustat, and county-level demographic data from the U.S. Census Bureau. I begin with all U.S. public firms from Compustat for the period 2014-2020. My data starts from 2014, as this is the first year for which YCOM data is available, and ends in 2020. To match a firm to its corresponding county-level CCSN measure, I use the U.S. ZIP code of the firm's headquarters from Compustat.[20] The intersection of these data sets constitutes my final sample.

Table 1 Panel A presents the sample selection procedure, and Panel B reports the sample distribution across years. My initial sample consists of 78,850 firm-year observations covering all U.S. incorporated firms from Compustat from 2014 to 2020. I first exclude 23,202 firm-year observations for firms that are not headquartered in the U.S. Consistent with prior literature, I drop 27,753 firm-year observations corresponding to financial (SIC codes 6000-6999) and utility (SIC codes 4900-4999) firms because these firms are highly regulated and may have different incentives for cash holdings. I exclude 83 firm-year observations with missing information on YCOM. I exclude 6,072 firm-year observations with missing values on either cash holdings or control variables necessary to run the baseline regression model. After applying these filters, I end up with a final sample of 21,740 firm-year observations covering 4,580 distinct firms. To mitigate the influence of outliers, I winsorize all continuous variables except *CCSN* at the 1st and 99th percentiles.

Table1: Sample Selection and Distribution

Table 1 reports sample selection and distribution. Panel A provides the sample selection procedure for our main sample. Panel B provides the sample distribution by year during the sample period 2014-2020.

Panel A: Sample selection	
Starting with all firm-year observations in Compustat	78,850
Excluding firms not headquartered in the U.S.	-23,202
Excluding financial (SIC codes 6000-6999) and utility firms (SIC codes 4900-4999)	-27,753
Excluding firm-year observations with missing information on YCOM	-83
Excluding firm-year observations with missing cash holdings or control variables	-6,072

[20] One concern is that Compustat doesn't report firms' historical headquarter locations. However, according to Pirinsky and Wang (2006), less than 3% of firms changed their headquarter locations.

Final sample	21,740
Panel B: Sample distribution	
Fiscal year	
2014	3,332
2015	3,292
2016	3,155
2017	3,055
2018	3,020
2019	2,954
2020	2,932

3.2 Measure of Climate Change Social Norms

Prior literature on social norms typically proxies managers' social norms using survey data on geography-based social norms (Cialdini et al., 1990; Hilary and Hui, 2009; Kumar et al., 2011; Labovitz and Hagedorn, 1973). For example, Kumar et al. (2011) proxy managers' gambling attitudes using the local social norms on gambling. Given that managers' personal norms on climate change are neither public knowledge nor directly observable, following prior literature (e.g., Hilary and Hui, 2009), I assume that county-level CCSN influences local cultural norms and consequently affects managers' personal norms on climate change, even if they may not personally believe in climate change.

I measure county-level CCSN using survey data from YCOM between 2014 and 2020. Specifically, my measure is constructed based on responses to the following three questions:(1) "Estimate percentage who are somewhat/very worried about global warming?", (2) "Estimate percentage who think that global warming is happening", and (3) "Estimate percentage who think global warming will harm people in the U.S. a moderate amount/a great deal". These questions are documented in all four waves of the survey. I extract the first major component using the principal component analysis and use it as my principal measure for CCSN. Thus, a higher value suggests a greater level of CCSN, and vice versa. For robustness, I employ several alternative measures of CCSN and discuss them in more detail in Section 4.3.6.[21]

3.3 Measures of Cash Holdings

I measure corporate cash holdings using several proxies that are widely used in the literature. Specifically, following prior literature (Bates et al., 2009; Foley et al., 2007; Hanlon, Maydew, and Saavedra, 2017), I employ the following cash ratios: (1) cash-to-assets, (2) cash-to-net assets, where net assets are defined as the difference between total assets and the sum of cash and marketable securities, and (3) the natural logarithm of one plus cash-to-net assets.[22] Following prior literature, I employ the natural logarithm of one plus cash-to-net assets as my principal measure, with other measures being used in the robustness tests.

3.4 Regression Model

Following prior literature (e.g., Bates et al., 2009; Opler et al., 1999; Hanlon et al., 2017), I adopt the following model to examine the influence of CCSN on corporate cash holdings:

$$(1)\quad Cash_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Size_{it} + \alpha_3 MTB_{it} + \alpha_4 Lev_{it} + \alpha_5 CF_{it} + \alpha_6 CF\_sd_{it} + \alpha_7 Nwc_{it} + \alpha_8 Divi_{\ it} + \alpha_9 RD_{it} + \alpha_{10} Capx_{it} + \alpha_{11} Aqc_{it} + \Sigma\beta_i Fixed\ effects + \varepsilon_{it}$$

[21] Given that managers' social norms are neither directly observable nor public knowledge, I argue that CCSN can capture managers' climate change-related social norms based on existing literature (e.g., Kumar et al., 2011; McGuire et al., 2012). However, there is a caveat regarding this measure because managers located in the same county could have divergent beliefs.

[22] Prior research suggests that cash-to-sales is another possible measure for cash holdings. Similar to Bates et al. (2009), using this measure does not affect my finding materially.

where i, and t denote firm and year, respectively; *Cash* and *CCSN* denote corporate cash holdings and climate change social norms, respectively, as defined in Sections 3.2 and 3.3.

I control for variables found by the existing research to influence cash holdings. Specifically, I control for firm size (*Size*), defined as the natural logarithm of total assets, because prior research suggests that large firms have more access to financing relative to small firms, mitigating their needs to hold cash (Opler et al., 1999). I include the market-to-book ratio (*MTB*), defined as the market value of equity divided by the book value of equity, because growth firms require more cash to fund their growth. I control for leverage (*Lev*), measured as the sum of long-term debt plus current debt scaled by total assets, because it is likely to affect cash holdings in opposing directions. Prior research finds that firms with more cash flows from operating activities hold less cash while firms with more volatile cash flows hold more cash. I, therefore, include both operating cash flows (*CF*), defined as cash flows from operating activities scaled by total assets, and the volatility of cash flows (*CF_sd*), defined as the standard deviation of operating cash flows over the past four years. I include net working capital (*Nwc*), measured as the difference between working capital and cash holdings, deflated by total assets. Consistent with prior literature (e.g., Opler et al., 1999), I expect firms with more net working capital hold less cash due to their easy access to liquid assets. I control for dividend payout by including an indicator variable (*Divi*) equal to one if the firm paid dividends during the year and zero otherwise. I finally control for a set of investment variables, including research and development expenses scaled by total assets (*RD*), capital expenditures scaled by total assets (*Capx*), and acquisition expenses scaled by total assets (*Aqc*). I also include year and industry dummy variables to control industry- (using 2-digit SIC codes) and year-level fixed effects. I cluster standard errors at the county level to address serial correlation in the error term.[23] The main coefficient of interest is α_1. I expect the sign of α_1 to be positive if *CCSN* positively influences corporate cash holdings. Appendix A presents the detailed definitions of the variables used in the study.

4. Empirical Results

4.1 Descriptive Statistics

Table 2 Panel A reports comparisons of the top and bottom ten counties in the U.S out of the 1,931 counties in my sample. As observed from Table 2 Panel A, I find that the top three counties with the highest CCSN over the sample period are Bronx, NY, Alameda, CA, and New York, NY, respectively, whereas Overton, TN, Sheridan, WY, and Campbell, TN are the bottom three counties with the lowest CCSN.

Panel B of Table 2 reports descriptive statistics of the main variables included in my analysis. The mean (median) value of cash-to-assets (*Cash1*) is 26.3% (14.5%), consistent with those reported in the literature (e.g., Bates et al., 2009). The means (medians) of *Cash2* and *Cash3* are 1.876 (0.169) and 0.48 (0.156), respectively. The mean (median) value of *CCSN* is -0.045 (0.052), and the standard deviation is 1.684, suggesting substantial variation in the variable *CCSN* across counties.[24]

Table 2 Panel C presents the Pearson pairwise correlations between the variables in my main tests. As expected, I find that three measures of cash holdings are significantly positively correlated with each other ($p<0.01$). In particular, I find that *CCSN* is significantly positively

[23] My findings remain qualitatively unchanged when standard errors are clustered at the firm level, as reported in Section IV.G.

[24] It is worthwhile to note that untabulated results suggest that *CCSN* has not only a cross-sectional variation but also a temporal variation.

associated with all three measures of cash holdings, providing some preliminary (univariate) support for H1. The signs of correlations between cash holdings and control variables are largely consistent with prior literature.

Table 2: Summary Statistics and Correlations

Table 2 reports the summary statistics and correlations of the key variables. Panel A reports the comparison of the top and bottom ten U.S. counties as ranked by *CCSN*. Panel B provides the descriptive statistics for the variables used in our main analysis. Panel C reports the Pearson pairwise correlations for the key variables. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Panel A: Comparison of the Top and Bottom U.S. Counties as Ranked by CCSN

Top Counties		Bottom Counties	
Rank		Rank	
1	Bronx County, NY	1931	Overton County, TN
2	Alameda County, CA	1930	Sheridan County, WY
3	New York County, NY	1929	Campbell County, TN
4	District of Columbia, DC	1928	Fayette County, AL
5	San Francisco County, CA	1927	Natrona County, WY
6	Suffolk County, MA	1926	Burke County, GA
7	Hudson County, NJ	1925	Lee County, MS
8	Honolulu County, HI	1924	Jennings County, IN
9	Montgomery County, MD	1923	Laramie County, WY
10	San Mateo County, CA	1922	Cherokee County, AL

Panel B: Descriptive statistics

	N	Mean	Std. Dev.	p25	Median	p75
Cash1	21740	.263	.283	.045	.145	.402
Cash2	21740	1.876	6.289	.047	.169	.672
Cash3	21740	.48	.773	.046	.156	.514
CCSN	21740	-.045	1.684	-1.125	.052	1.263
Size	21740	5.588	2.823	3.839	5.902	7.589
MTB	21740	6.882	30.77	1.254	1.858	3.361
Lev	21740	.531	1.753	.035	.232	.438
CF	21740	-2	7.598	-.41	.041	.101
CF_sd	21740	1.467	4.715	.022	.064	.331
Nwc	21740	-.726	4.807	-.108	-.006	.103
Divi	21740	.292	.455	0	0	1
RD	21740	.117	.28	0	.008	.105
Capx	21740	.04	.058	.008	.022	.047
Aqc	21740	.021	.059	0	0	.005

Panel C: Pairwise correlations

Variables	(Cash1)	(Cash2)	(Cash3)	(CCSN)	(Size)	(MTB)	(Lev)	(CF)	(CF_sd)	(Nwc)	(Divi)	(RD)	(Capx)	(Aqc)
Cash1	1.000													
Cash2	0.630***	1.000												
Cash3	0.922***	0.860***	1.000											
CCSN	0.256***	0.126***	0.216***	1.000										
Size	-0.322***	-0.178***	-0.281***	0.015**	1.000									
MTB	0.063***	0.024***	0.050***	0.012*	-0.392***	1.000								
Lev	-0.035***	-0.020***	-0.027***	-0.016**	-0.351***	0.587***	1.000							
CF	-0.393***	-0.532***	-0.500***	-0.056***	0.450***	-0.563***	-0.481***	1.000						
CF_sd	0.339***	0.391***	0.404***	0.083***	-0.385***	0.297***	0.253***	-0.502***	1.000					
Nwc	-0.023***	-0.011*	-0.021***	-0.006	0.412***	-0.734***	-0.830***	0.587***	-0.319***	1.000				
Divi	-0.300***	-0.168***	-0.265***	-0.133***	0.456***	-0.100***	-0.088***	0.172***	-0.189***	0.105***	1.000			
RD	0.411***	0.220***	0.369***	0.116***	-0.392***	0.287***	0.259***	-0.491***	0.324***	-0.295***	-0.232***	1.000		
Capx	-0.234***	-0.152***	-0.215***	-0.149***	0.107***	-0.037***	-0.008	0.103***	-0.068***	0.025***	0.039***	-0.119***	1.000	
Aqc	-0.180***	-0.098***	-0.156***	-0.034***	0.175***	-0.053***	-0.036***	0.093***	-0.083***	0.051***	0.086***	-0.104***	-0.060***	1.000

4.2 Main Results

Table 3 presents the estimates for Equation (1) for each of the three dependent variables, with my focus on *Cash3*.[25] The explanatory power of Equation (1) for the three dependent

[25] For the sake of brevity, the coefficients on the indicator variables on industry and year are not reported.

variables is large and consistent with each other, ranging from 0.5094 to 0.5659. Across all specifications, *CCSN* is significantly positively related to corporate cash holdings, whether measured by *Cash1*, *Cash2*, or *Cash3*, with the coefficients ranging from 0.024 to 0.197. Specifically, the coefficient on *CCSN* in Column 3 is positive and significant at the 1% level (coef. = 0.050, t-stat.= 8.87). The positive relationship between *CCSN* and cash holdings is also economically meaningful. In terms of magnitude, a one standard deviation increase in *CCSN* is associated with a 17.5% increase in *Cash3*.[26] In terms of economic magnitude, this translates to an increase of 8.4% in cash holdings for an average firm that reports a mean *Cash3* of 0.48. For comparison, the influence of CCSN is comparable to that of the Effective Repatriation Tax Rate (*ERTR*, hereafter), documented in Foley et al. (2007), who show that a one standard deviation increase in *ERTR* is associated with a 12% increase in cash holdings.

In terms of control variables, I find that the signs of the estimated coefficients of the control variables are largely consistent with those reported in the extant literature. Consistent with prior literature (e.g., Bates et al., 2009, Lyandres and Palazzo, 2016), I find that both the volatility of cash flow (*CF_sd*) and net working capital (*Nwc*) are positively associated with cash holdings, while cash flows (*CF*), dividend paying dummy (*Divi*), capital expenditures (*Capx*), and acquisition expenses (*Aqc*) are negatively associated with cash holdings across specifications. The signs on firm size (*Size*) and R&D expenses (*RD*) are sensitive to the dependent variable employed.

[26] The influence of a one standard deviation increase in *CCSN* on cash holdings is calculated as: 0.050 (coefficient reported in Table 3) *1.684 (standard deviation of *CCSN* as reported in Table 2)/0.48 (mean of *Cash3* as reported in Table 2) = 17.5%.

Overall, these findings consistently show the positive association between CCSN and corporate cash holdings across specifications, highlighting the important role of CCSN in influencing corporate cash holdings.

Table 3: The influence of CCSN on Corporate Cash Holdings

Table 3 reports the estimated influence of CCSN on corporate cash holdings. The dependent variables are *Cash1, Cash2*, and *Cash3*, respectively. Our main explanatory variable is *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1	2	3
	Cash1	Cash2	Cash3
CCSN	**0.024***** **(10.21)**	**0.197***** **(5.39)**	**0.050***** **(8.87)**
Size	-0.004*** (-2.96)	0.146*** (5.23)	0.002 (0.61)
MTB	0.018*** (11.71)	-0.053* (-1.77)	0.022*** (5.89)
Lev	-0.024*** (-7.14)	-0.154 (-1.49)	-0.046*** (-4.64)
CF	-0.011*** (-16.13)	-0.593*** (-18.11)	-0.053*** (-20.98)
CF_sd	0.004*** (4.28)	0.195*** (7.47)	0.019*** (6.86)
Nwc	0.010*** (9.42)	0.475*** (10.87)	0.045*** (12.66)
Divi	-0.056*** (-8.53)	-0.932*** (-9.77)	-0.152*** (-10.04)
RD	0.058*** (3.52)	-3.444*** (-6.91)	-0.065 (-1.32)
Capx	-0.476*** (-9.95)	-6.984*** (-7.45)	-1.261*** (-9.68)
Aqc	-0.495*** (-20.47)	-4.624*** (-11.31)	-1.047*** (-16.64)
Constant	Y	Y	Y
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Obs.	21740	21740	21740
adj. R^2	0.5228	0.5094	0.5659

4.3 Endogeneity Issues and Robustness Checks

Like other empirical studies, my baseline regression model is subject to endogeneity concerns. While I am not concerned about reverse causality because it seems unlikely that corporate cash holdings influence county-level CCSN, my model may suffer omitted correlated variable bias, as the level of CCSN could be correlated with some unobserved regional characteristics that also influence firms' cash holdings. My findings may also be biased if there are measurement errors in my key independent variable (*CCSN*). I, therefore, address these endogeneity concerns in several different ways as detailed below.

4.3.1 A DiD Research Design

I perform a DiD analysis to further validate the positive association between CCSN and corporate cash holdings. Following prior literature, I exploit the occurrence of two hurricanes (Harvey and Irma)[27] in 2017 as a plausibly exogenous shock to amplify CCSN because they may influence the propensity of managers to act on climate-induced extreme weather events. Following Dessaint and Matray (2017), I divide all counties into three categories: affected counties, neighboring counties, and the rest of the U.S. I classify a county as affected if the county is designated as eligible for either public or individual assistance by the Federal Emergency Management Agency (FEMA).[28] FEMA designated 154 out of 367 counties in the states of Florida, South Carolina, and Texas as eligible to apply for disaster assistance in 2017.

As noted by Dessaint and Matray (2017), I drop firms located in the affected counties in my analysis because the impact on cash holdings may be directly attributable to the occurrence of natural disasters rather than CCSN, thus distorting my inferences. I also drop firms headquartered in the neighboring counties in the disaster states because they are likely to be indirectly affected by the hurricanes due to regional spillover effects. For example, although Dorchester, SC was the only county directly hit by Hurricane Irma in South Carolina, counties even in the northwestern part of the state have also been designated as eligible for public assistance. One possible

[27] Hurricane Maria is not considered here because it did not hit the U.S. mainland in 2017.
[28] See https://www.fema.gov/disaster for more details.

explanation is that these counties are indirectly affected by the hurricane. Therefore, I assign firms in the neighboring states to the treated group and firms in the rest of the U.S. mainland to the control group because the motivation to act upon CCSN of the former firms is most likely to change due to the influence of hurricanes (but not directly or indirectly affected by the hurricanes) relative to that of the latter firms. Specifically, I estimate the following model:

$$
\begin{aligned}
(2)\qquad Cash_{it} = {} & \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Post_t + \alpha_3 Neighbor_t + \alpha_4 Post_t * Neighbor_t \\
& + \alpha_5 CCSN_{it} * Neighbor_t + \alpha_6 CCSN_{it} * Post_t + \alpha_7 CCSN_{it} * Post_t * Neighbor_t \\
& + \alpha_8 Size_{it} + \alpha_9 MTB_{it} + \alpha_{10} Lev_{it} + \alpha_{11} CF_{it} + \alpha_{12} CF\_sd_{it} + \alpha_{13} Nwc_{it} \\
& + \alpha_{14} Divi_{\,it} + \alpha_{15} RD_{it} + \alpha_{16} Capx_{it} + \alpha_{17} Aqc_{it} + \Sigma\beta_i Fixed\ effects + \varepsilon_{it}
\end{aligned}
$$

where *Post* is an indicator variable equal to one in the years 2018-2020 and zero in the years 2014-2016. *Neighbor* is an indicator variable equal to one if the firm is headquartered in the neighborhood of a disaster state hit by Hurricanes Harvey or Irma and zero otherwise. *Cash, CCSN, Size, MTB, Lev, CF, CF_sd, Nwc, Divi, RD, Capx,* and *Aqc* are as previously defined. My variable of interest is *CCSN*Post*Neighbor*. α_7 is a difference-in-differences estimate which captures the change in neighboring firms' cash holdings before and after the hurricanes relative to the corresponding change in faraway firms' cash holdings. Given the increased influence of CCSN following large disasters, I expect the coefficient on *CCSN*Post*Neighbor* to be positive if neighboring firms with high CCSN increase cash holdings after the occurrence of hurricanes.

I report the DiD results in Panel A of Table 4. As can be seen from Panel A, the coefficient on *CCSN*Post*Neighbor* is positive and significant at the 1% level (coef. = 0.036, t-stat.= 3.41), suggesting that CCSN heightened by hurricanes leads neighboring firms to accumulate cash holdings relative to the control firms during the post-disaster periods.

I proceed to examine whether the crucial parallel trends assumption holds. This analysis tests the possibility that the post-disaster changes in cash holdings are ascribed to trending differences between firms in the treated and control groups before the occurrence of hurricanes rather than the enhanced strength of CCSN. Table 4 Panel B reports the results. These results reflect the dynamics and persistence of the effects of hurricane-induced CCSN on firms' cash holding behaviors. I find that the coefficients on *D(t=-3)*Neighbor*CCSN*, *D(t=-2)*Neighbor*CCSN*, and *D(t=-1)*Neighbor*CCSN* are not significantly different from zero, suggesting that there are no preexisting differences between firms in the treated and control groups in the previous three years. In contrast, I find that the coefficients on *D(t=1)*Neighbor*CCSN* and *D(t=2) *Neighbor*CCSN* are significant at the 5% and 1% levels, respectively. The insignificant coefficient on *D(t=3)*Neighbor*CCSN* suggests that the impact completely fades away after two years. Overall, these results lend support to my main findings and facilitate a causal interpretation between CCSN and corporate cash holdings.

Table 4: A Difference-in-Differences Analysis

Table 4 reports the results for the DiD analysis. Panel A reports the DiD regression results on the relationship between *CCSN* and cash holdings. The dependent variable is *Cash3*. Our main explanatory variable is the three-way interaction *CCSN*Neighbor*Post*. Panel B reports the results for the verification of the parallel trends assumption. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Panel A: DiD results

	1 Cash3
CCSN	-0.005 (-0.34)
Neighbor*Post	0.015 (1.24)
CCSN*Post	-0.019** (-2.44)
CCSN*Neighbor	0.033*** (3.80)
CCSN*Neighbor*Post	**0.036*** (3.41)**
Controls	Y
Fixed Effects	Y
Obs.	17433

adj. R^2	0.8771

Panel B: Parallel trends assumption

	1 Cash3
D(t=-3) *Neighbor*CCSN	0.013 (1.27)
D(t=-2) *Neighbor*CCSN	0.008 (0.36)
D(t=-1) *Neighbor*CCSN	0.012 (0.77)
D(t=1) *Neighbor*CCSN	0.028** (2.17)
D(t=2) *Neighbor*CCSN	0.036*** (2.93)
D(t=3) *Neighbor*CCSN	0.027 (1.37)
Controls	Y
Fixed Effects	Y
Obs.	17957
adj. R^2	0.5747

4.3.2 An Instrumental Variable Approach

I further address such endogeneity concerns using a two-stage least squares (2SLS) regression approach with three different IVs. First, I follow Baldauf, Garlappi, and Yannelis (2020) and use the percentage of individuals in a ZIP code who vote for the Republican Party (*Repubpp*) as my first IV. This IV is correlated with the *CCSN*, as political ideology is shown to be associated with individuals' climate change beliefs (Lee et al., 2015). However, it is unlikely to affect corporate cash holding policies, satisfying both relevance and exclusion criteria.[29]

I report the results in the first two columns of Table 5. As shown in Table 5, I find that *Repubpp* is significantly negatively associated with *CCSN* in the first-stage regression, consistent with Baldauf et al. (2020). In the second-stage regression, I report results that are consistent with

[29] I acknowledge that the exclusion criterion is not mathematically testable.

those reported in the baseline regression. In addition, the Kleibergen-Papp Wald F statistic is well above the threshold value, mitigating the concern of a weak instrument.

My second IV is the adoption of the CAPs. I define an indicator variable *CAP* equal to one if a state has CAPs in place or is in the process of designing one, and zero otherwise.[30] Given that thirty-four states in the U.S. have adopted the CAPs that aim to take measurable actions against climate change, I reason that CCSN in these states with CAPs are likely to increase because public policy can affect social norms (Nyborg, 2003). In addition, the adoption of CAPs at the state level is mainly related to climate change adaptation and greenhouse gas mitigation. Therefore, it is unlikely that the state-level adoption of the CAPs is related to firm-level cash holdings. My third IV is the average county-level CCSN (*AvgCCSN*) within a state (excluding the focal county). The reasoning here is that a county's CCSN is likely correlated with those of surrounding counties within the same state. However, corporate cash holdings are unlikely to be affected directly by the CCSN of surrounding counties. Together, these arguments suggest that both IVs satisfy the relevance and exclusion criteria.

Table 5 Columns 3 to 4 report the IV regression results. In the first-stage regression, as reported in Column 3 of Table 5, I find that both IVs are significantly positively associated with *CCSN*. Moreover, the Kleibergen-Papp Wald F statistic is greater than the critical value of the Stock and Yogo (2005) statistic, suggesting that both IVs are not weak instruments. The partial R-square is 0.404, indicating that both IVs jointly explain a large portion of the variation in *CCSN*.

Column 4 of Table 5 reports the second-stage regression results. I find that the results yielded from the second-stage regression are in line with the baseline regression results in Table

[30] The data is sourced from https://www.c2es.org/document/climate-action-plans/.

3. However, the coefficient is greater in magnitude than that reported in Table 3, indicating a downward bias in my baseline regression. Furthermore, the p-value of Hansen J statistic is 0.682, suggesting that there is no over-identification concern in my model specification. Overall, the results from the IV approach provide further support to my main findings by mitigating the omitted correlated variable bias.

Table 5: Instrumental Variable Approach

Table 5 reports the estimated effects of CCSN on cash holdings using an IV approach using three different IVs. Columns 1 and 3 report the first-stage regression results while Columns 2 and 4 report the second-stage regression results. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	(1) First stage CCSN	(2) Second stage Cash3	(1) First stage CCSN	(2) Second stage Cash3
CCSN		**0.051*** (19.68)**		**0.070*** (18.49)**
Size	-0.014*** (-7.10)	0.002 (1.21)	0.073*** (20.30)	0.001 (0.18)
MTB	0.010*** (4.51)	0.022*** (9.07)	0.027*** (6.38)	0.021*** (8.49)
Lev	-0.017*** (-4.36)	-0.046*** (-7.16)	-0.034*** (-8.52)	-0.045*** (-7.01)
CF	0.001 (1.24)	-0.053*** (-33.20)	-0.003** (-2.31)	-0.053*** (-33.22)
CF_sd	-0.001 (-0.45)	0.019*** (10.45)	0.007*** (3.81)	0.019*** (10.37)
Nwc	-0.003* (-1.78)	0.045*** (16.02)	-0.012*** (-3.50)	0.045*** (16.24)
Divi	-0.058*** (-5.70)	-0.152*** (-24.32)	-0.109*** (-5.61)	-0.144*** (-22.56)
RD	0.012 (0.72)	-0.066** (-2.19)	0.050 (1.47)	-0.070** (-2.33)
Capx	-0.311*** (-4.36)	-1.260*** (-17.06)	-0.372** (-2.54)	-1.232*** (-16.69)
Aqc	0.062 (0.94)	-1.046*** (-29.88)	-0.265** (-2.17)	-1.031*** (-29.09)
Repubpp	-9.041*** (-307.41)			

AvgCCSN			0.683***	
			(98.90)	
CAP			0.109***	
			(4.57)	
Kleibergen-Papp Wald F	94501.42		6532.88	
Partial R^2			0.404	
Hansen J (p-value)				0.682
Constant	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	21740	21740	21731	21731
adj. R^2	0.8906	0.5674	0.5940	0.5662

4.3.3 Changes Regressions

My main empirical specification estimates the relationship between CCSN and cash holdings using a levels-on-level specification. To further address that time-invariant omitted correlated variables may drive my results, I follow prior literature (e.g., Bates et al., 2009; Foley et al., 2007) and employ two changes-on-changes specifications.

Column 1 of Table 6 reports the estimation results of estimating a "simplified" changes-on-changes specification, while Column 2 reports a standard changes-on-changes specification. Given that I use changes rather than levels specifications, the sample size reduces significantly. In both Columns 1 and 2, I find that the coefficients on *ΔCCSN*, my primary variable of interest, are positive and significant at least at the 5% level (coef. = 0.048, t-stat.= 2.51 and coef. = 0.038, t-stat.= 2.30, respectively). These results provide supportive evidence for the view that county-level variation in CCSN influences corporate cash holdings.

Table 6: Changes Regressions

Table 6 reports the estimated effects of CCSN on cash holdings using changes regression. Column 1 reports the estimated effect using a "simplified" changes-on-changes regression. Column 2 reports the results under a standard changes-on-changes specification. The prefix Δ denotes the change in a variable. The dependent variable is *ΔCash3*. Our main explanatory variable is *ΔCCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1		2
	ΔCash3		ΔCash3
ΔCCSN	**0.048****	**ΔCCSN**	**0.038****
	(2.51)		**(2.30)**
Size	0.003	ΔSize	-0.024*
	(0.15)		(-1.68)
MTB	-0.007**	ΔMTB	-0.012
	(-2.18)		(-0.87)
Lev	-0.059	ΔLev	-0.076*
	(-1.32)		(-1.80)
CF	-0.078***	ΔCF	-0.066***
	(-10.07)		(-9.41)
CF_sd	0.017*	ΔCF_sd	0.023***
	(1.66)		(2.92)
Nwc	0.026	ΔNwc	0.042**
	(1.00)		(2.18)
Divi	-0.084	ΔDivi	-0.125*
	(-0.95)		(-1.79)
RD	-0.495***	ΔRD	0.171
	(-2.64)		(1.50)
Capx	-1.033**	ΔCapx	-1.464***
	(-2.07)		(-4.41)
Aqc	-1.041***	ΔAqc	-0.771***
	(-3.56)		(-4.34)
Constant	Y	Constant	Y
Industry FE	Y	Industry FE	Y
Year FE	Y	Year FE	Y
Obs.	1846	*Obs.*	1539
adj. R^2	0.3610	*adj.* R^2	0.4936

4.3.4 Subsample Analyses

Following Hilary and Hui (2009), I re-estimate my model using more homogenous subsamples. I split the sample and perform additional tests to ensure that my findings are not driven by firms concentrated in any specific locations or time periods. First, prior literature has identified the impact of political views on climate change perception (e.g., Howe et al., 2015). Therefore, it is important to demonstrate that my results are not driven by firms located in counties in Democratic states. To this end, I restrict my sample to firms in Republican states to ensure that my results are not driven by firms in Democratic states. Second, I exclude California from my analysis because it is the largest Democratic state and accounts for the largest number of observations. Third, in my final set tests, I drop the Gulf States (i.e., Alabama, Florida, Louisiana, Mississippi, and Texas) to ensure that my findings are not driven by firms located in these states which are particularly susceptible to climate change relative to other states. Fourth, the Trump administration withdrew the U.S. from the Paris Agreement in 2017 and called climate change a hoax, which may negatively impact CCSN, especially for counties with lower CCSN.[31] However, from an empirical perspective, the impact of these confounding events is still unclear and difficult to control. To address this concern, I partition my sample into two subperiods (pre-2017 and post-2017) and investigate whether my findings hold in these two subsamples.

Table 7 reports the results for subsample analyses. Across all specifications, I find that the coefficients on *CCSN* are positive and significant at the 1% level, ranging from 0.028 to 0.053. Together, these results further validate my main findings.

Table 7: Subsample Analyses

Table 7 reports the estimated effects of CCSN on cash holdings using more homogeneous subsamples. Column 1 reports the regression results after excluding firms located in the Democratic States. Column 2 reports the results after excluding California. Column 3 reports the results after excluding the Gulf States. Columns 4 to 5 reports the results for the pre-2017 and the post-2017 period, respectively. The dependent variable is *Cash3*. Our main explanatory variable is *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1 Republican States	2 Excluding California	3 Excluding the Gulf States	4 Pre-2017	5 Post-2017
CCSN	**0.028*** (3.99)**	**0.040*** (7.72)**	**0.045*** (7.67)**	**0.045*** (7.40)**	**0.053*** (8.61)**

[31] The former U.S. President Trump made the statement regarding the withdrawal of the U.S. from the Paris Agreement on June, 1, 2017 (See https://www.nytimes.com/2017/06/01/climate/trump-paris-climate-agreement.html for more details).

Size	-0.008	-0.004	0.001	0.006	-0.002
	(-1.41)	(-1.21)	(0.35)	(1.61)	(-0.39)
MTB	0.026***	0.019***	0.024***	0.014***	0.029***
	(3.32)	(4.33)	(5.60)	(2.85)	(6.47)
Lev	-0.009	-0.034***	-0.061***	-0.040***	-0.052***
	(-0.55)	(-3.17)	(-5.28)	(-3.57)	(-4.14)
CF	-0.048***	-0.053***	-0.056***	-0.051***	-0.055***
	(-9.00)	(-18.25)	(-21.58)	(-18.52)	(-16.28)
CF_sd	0.022***	0.018***	0.019***	0.021***	0.017***
	(3.14)	(5.44)	(6.74)	(6.27)	(4.52)
Nwc	0.044***	0.047***	0.042***	0.041***	0.047***
	(6.47)	(11.59)	(10.33)	(9.47)	(9.59)
Divi	-0.077***	-0.125***	-0.157***	-0.150***	-0.153***
	(-3.59)	(-8.56)	(-9.38)	(-9.71)	(-8.92)
RD	-0.083	-0.038	-0.073	-0.087	-0.042
	(-0.71)	(-0.66)	(-1.48)	(-1.53)	(-0.68)
Capx	-0.599***	-1.125***	-1.608***	-1.076***	-1.494***
	(-4.45)	(-8.58)	(-9.96)	(-8.57)	(-8.41)
Aqc	-0.657***	-0.903***	-1.115***	-1.089***	-1.038***
	(-9.24)	(-15.53)	(-15.74)	(-15.03)	(-14.34)
Constant	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Obs.	5925	17885	17866	9779	11961
adj. R2	0.5578	0.5617	0.5815	0.5525	0.5782

4.3.5 Additional Control Variables

Prior research indicates that several demographic and political factors may influence CCSN, such as geography, gender, household income, education, and political orientation (e.g., Barr, 2007; Howe et al., 2015; Lee et al., 2015; O'Connor et al., 1999). To mitigate the concern that variations in these variables instead of CCSN may result in increased cash holdings, I draw on county-level or state-level data for these variables from the U.S. Census Bureau and incorporate them into my regressions. Specifically, I consider the following variables, including the latitude and longitude of the county (*Lat* and *Lng*), the county-level proportion of the female population (*Feper*), county-level GDP per capita (*GDP*), county-level education measured by the percentage of individuals (age 25 and above) who have earned a bachelor's degree or higher (*College*), and the state-level dominant political orientation (*Political*).[32]

Table 8 presents the results after including demographic and political variables. I augment my baseline specifications by controlling for each variable separately in Columns 1 through 6 and collectively in Column 7. As observed from Table 8, the coefficients on *CCSN* remain positive and statistically significant across all specifications, mitigating the concern that *CCSN* may pick up the variation of other demographic or political variables.

Table 8: Additional Controls

Table 8 reports the estimated effects of CCSN on cash holdings after controlling for demographic and political variables. Column 1 reports the regression results after controlling for the latitude and longitude of a county. Column 2 reports the results after controlling for GDP per capita. Column 3 reports the results after controlling for the percentage of female population at the county level. Column 4 reports the results after controlling for educational attainment. Column 5 reports the results after controlling for political ideology. Column 6 reports the results after controlling for all these demographic and political variables simultaneously. The dependent variable is *Cash3*. Our main explanatory variable is *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1	2	3	4	5	6
	Lat and Lng	GDP	Fepp	College	Political	ALL
CCSN	**0.046***** **(8.63)**	**0.046***** **(7.60)**	**0.053***** **(9.94)**	**0.026***** **(4.26)**	**0.049***** **(8.03)**	**0.028***** **(4.03)**
Lat	0.005*** (2.87)					0.001 (0.63)
Lng	-0.001** (-2.12)					-0.001 (-1.00)
GDP		0.000 (0.88)				-0.000 (-0.74)
Fepp			-4.361*** (-4.53)			-3.545*** (-2.97)
College				0.006*** (6.18)		0.007*** (6.73)
Political					0.009	-0.005

[32] The dominant political view depends on the state-level presidential elections data in 2008, 2012, and 2016. Note that I don't use the 2020 presidential election data because it is usually deemed controversial. My results continue to hold when I use four or five years of election results (i.e., 2000, 2004, 2008, 2012, and 2016).

					(0.48)	(-0.23)
Controls	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	21740	18545	18808	21740	21740	18545
adj. R^2	0.5675	0.5648	0.5666	0.5700	0.5659	0.5723

4.3.6 Alternate Measures of CCSN

Since *CCSN* is a multi-dimensional construct and the operationalization of this concept is challenging, it is plausible that my primary measure in the preceding analyses may not capture the important characteristics of CCSN precisely. To mitigate this concern, I adopt two different approaches. First, I create a scaled quintile rank for the *CCSN* variable (*CCSN5*).[33] Specifically, I rank observations based on the value of *CCSN* by year into 5 categories ranging from 0 to 4, and scaled the generated rank by 4, leading to a *CCSN* rank variable ranging from 0 to 1. Thus, a higher rank represents higher CCSN, and vice versa. Using a scaled quintile ranked variable is also a feasible means to mitigate potential measurement errors. Second, rather than relying on the aggregated *CCSN* index, I use its three individual components and further explore the robustness of my main findings.

I report the results for alternate measures of CCSN in Table 9. I find that the coefficient on *CCSN5* is positive and significant at the 1% level (coef. = 0.293, t-stat.= 8.70), albeit larger in magnitude than the coefficients on the variable reported in Table 3. Turning to three individual components of CCSN (i.e., *Happening, HarmUS,* and *Worried*), I document that each component is significantly positively associated with cash holdings, consistent with my main findings.

[33] My results continue to hold if I employ a scaled decile ranked variable.

Table 9: Alternate Measures for CCSN

Table 9 reports the regression results for alternate measures of CCSN. The dependent variable in Column 1 is a scaled quintile ranked variable of *CCSN*. The dependent variables in Columns 2 to 4 are three individual components of *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1 CCSN5	2 Happening	3 HarmUS	4 Worried
CCSN5	**0.293*** (8.70)**			
Happening		**0.012*** (8.42)**		
HarmUS			**0.013*** (8.84)**	
Worried				**0.011*** (8.64)**
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	21740	21740	21740	21740
adj. R^2	0.5660	0.5655	0.5656	0.5655

4.4 Cross-sectional Analyses

4.4.1 The Role of Financial Constraints

I proceed to investigate whether financial constraints moderate the relationship between CCSN and cash holdings. Earlier studies show that corporate cash holdings are closely related to the availability of external financing and internal funds (Froot, Scharfstein, and Stein, 1993; Holmstrom and Tirole, 1998). Thus, financially constrained firms have a stronger incentive to hold cash relative to their unconstrained counterparts (Almeida et al., 2004). Following prior literature, I proxy financial constraints using two different measures: (1) Whited and Wu (2006) (*WW*) index and (2) Hadlock and Pierce (2010) (*HP*) index. I construct two indicator variables based on the sample median values of *WW* and *HP* scores, respectively. Specifically, *WW* (*HP*) is an indicator variable equal to one if the firm's *WW* (*HP*) index is above the sample median and zero otherwise.[34] I employ the following specification to examine the moderating role of financial constraints:

$$(3) \qquad Cash_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Financially\ constrained_{it} + \alpha_3 CCSN_{it} * Financially\ constrained_{it} + \Sigma\gamma_i Controls + \Sigma\beta_i Fixed\ effects + \varepsilon_{it}$$

where *Financially constrained* refers to two different proxies of financial constraints: *WW* and *HP*. *Controls* is a set of control variables as previously defined.

As shown in Columns 1 and 2 in Table 10, I find that the coefficients on *CCSN* remain positive and statistically significant at the 1% level. Consistent with expectations, I also document that both *WW* and *HP* are positively associated with corporate cash holdings at the 1% level, respectively. Most importantly, the coefficients on both *CCSN*WW* (coef. = 0.052, t-stat.= 7.24) and *CCSN*HP* (coef. = 0.062, t-stat.= 7.74) are positive and significant at the 1% level, suggesting that the positive relationship between CCSN and cash holdings is more pronounced for financially constrained firms.

4.4.2 The Role of Media Coverage

I next examine the moderating role of media coverage of climate uncertainty on the relationship between CCSN and corporate cash holdings. Research on social norms shows that traditional media influences norm perceptions (Spartz et al., 2017). In addition, the role of media coverage in monitoring firm behaviors and affecting corporate decisions has been extensively documented in the finance literature (e.g., Miller, 2006). Following prior literature (Baker, Bloom, and Davis, 2016; Engle, Giglio, Kelly, Lee, and Stroebel, 2020), I measure media coverage of

[34] The formulas to calculate both the *WW* and *HP* indexes are listed in Appendix A.

climate uncertainty by the frequency of articles in *The Wall Street Journal* containing the following two keywords: “climate change” or “global warming” and “uncertain” or “uncertainty”. Specifically, I construct a dummy variable *Media*, equal to one if the media coverage of climate uncertainty is greater than the sample median and zero otherwise. I expect that the positive association between CCSN and cash holdings is more pronounced during years with a heightened level of media coverage on climate uncertainty, as media coverage complements CCSN in influencing firms to increase cash holdings. To test this conjecture, I estimate the following model:

$$\text{(4)} \quad Cash_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Media_{it} + \alpha_3 CCSN_{it} * Media_{it} + \Sigma\gamma_i Controls + \Sigma\beta_i Fixed\ effects + \varepsilon_{it}$$

Table 10 Column 3 reports the results.[35] The coefficient on *CCSN* is significant at the 1% level, suggesting that there is a positive association between CCSN and corporate cash holdings even if the media coverage of climate uncertainty is low. More importantly, I find that the coefficient on *CCSN*Media* is positive and significant at the 5% level (coef. = 0.010, t-stat.= 2.08), suggesting that the positive relationship between CCSN and cash holdings is strengthened during years with a heightened level of media coverage of climate uncertainty.

4.4.3 The Effects of Climate Risk Exposure

As a final cross-sectional analysis, I investigate whether climate risk exposure motivates firms to increase their cash holdings. Given the higher financing costs in the post-disaster periods, firms with higher climate risk exposures are likely to accumulate more cash as a buffer against future financing costs. I adopt the firm-level climate risk measure (*cc_neg*) from Sautner, van Lent,

[35] *Media* is automatically dropped in the regression due to multicollinearity.

Vilkov, and Zhang (2020) to measure climate risk exposure.[36] For ease of interpretation, I take the absolute value of this measure. Specifically, I generate a dummy variable *Expo* equal to one if a firm's climate risk exposure is greater than the sample median during that year and zero otherwise. To test my conjecture, I estimate the following model:

$$(5) \qquad Cash_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Expo_{it} + \alpha_3 CCSN_{it} * Expo_{it} + \Sigma\gamma_i Controls + \Sigma\beta_i Fixed\ effects + \varepsilon_{it}$$

Table 10 Column 4 reports the results. I find that the coefficient on *CCSN* remains positive and significant at the 1% level. The coefficient on *CCSN*Expo* is positive and significant at the 1% level (coef. = 0.036, t-stat.= 3.82), suggesting that the positive relationship between CCSN and cash holdings is strengthened for firms with a higher climate risk exposure.

Table 10: Cross-sectional Analyses

Table 10 reports the results of the cross-sectional analyses. Columns 1 and 2 report how financial constraints (proxied by the *WW* index and *HP* index, respectively) moderate the relationship between CCSN and cash holdings. Column 3 reports the results of how media coverage of climate uncertainty moderates the relationship between CCSN and cash holdings. Column 4 reports how climate risk exposure moderates the examined association. Our main variables of interests are *CCSN*WW, CCSN*HP, CCSN*Media,* and *CCSN*Expo*, respectively. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1 WW index	2 HP index	3 Media Coverage	4 Climate risk exposure
CCSN	0.015*** (3.69)	0.017*** (3.98)	0.044*** (7.60)	0.039*** (8.07)
WW	0.180*** (10.91)			
CCSN*WW	**0.052*** (7.24)**			
HP		0.262*** (12.38)		
CCSN*HP		**0.062*** **		

[36] These data are drawn from https://osf.io/fd6jq/.

		(7.74)		
Media			-	
CCSN*Media			**0.010** (2.08)**	
Expo				0.032* (1.66)
CCSN*Expo				**0.036*** (3.82)**
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	21740	21720	21720	21720
adj. R^2	0.5744	0.5843	0.5666	0.5679

4.5 Sources of Cash Holdings

I next proceed to examine the sources of cash. Prior literature suggests that an increase in cash holdings may coincide with the disappearing dividends (Bates et al., 2009). Having established a positive association between CCSN and corporate cash holdings, I, therefore, conjecture that firms headquartered in higher CCSN counties are more likely to reduce the amount of dividend payouts and less likely to pay a dividend. In addition, there are additional sources of cash as identified in prior literature (e.g., Chay and Suh, 2009; Dessaint and Matray, 2017). For example, Chay and Suh (2009) find that firms may also reduce share repurchases to hoard more cash. As such, I consider whether CCSN influences net working capital (*Nwc*), capital expenditures (*Capx*), sales growth (*SG*), stock repurchases (*Repurchase*), and new financing (*Newfin*). I employ my baseline specification and apply it to each item separately. However, I exclude the same item on the right-hand side of the model when running regressions.

Table 11 reports the results. I find that the coefficients on *CCSN* in both Columns 1 and 2 are negative and significant at the 1% level (coef. = -0.128, t-stat.= -9.43 and coef. = -0.001, t-stat.= -3.67, respectively), suggesting that firms located in counties with higher CCSN reduce their dividend payouts and the likelihood to pay dividends, consistent with prior literature.[37] In addition, I find that the coefficients on CCSN in Models 3 and 4 are negative and significant at the 1% level (coef. = -0.059, t-stat.= -3.27; coef. = -0.002, t-stat.= -4.33), suggesting that these firms cut back net working capital and capital expenditures. However, I find no evidence that CCSN is related to sales growth, stock repurchases, and new financing.

Table 11: Sources of Cash

Table 11 reports the regression results for the possible sources of cash. The dependent variables from Columns 1 through 7 are the amount of dividend payouts, a dividend paying dummy, net working capital, capital expenditures, sales growth, stock repurchases, and new financing, respectively. Our main explanatory variable is *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1	2	3	4	5	6	7
	Dividend	Divi	Nwc	Capx	SG	Repurchase	Newfin
CCSN	**-0.128*** (-9.43)**	**-0.001*** (-3.67)**	**-0.059*** (-3.27)**	**-0.002*** (-4.33)**	**0.616 (0.93)**	**0.002 (0.78)**	**-0.095 (-0.60)**
Size	0.522*** (45.61)	0.000 (0.72)	0.140*** (7.62)	0.002*** (5.85)	-0.008 (-0.10)	0.032*** (19.16)	0.130 (1.13)
MTB	0.155*** (10.60)	0.003*** (6.70)	-0.029* (-1.67)	0.002*** (5.44)	-0.199 (-0.61)	0.016*** (8.15)	-0.237** (-2.45)
Lev	-1.271*** (-14.18)	-0.000 (-0.04)	-1.888*** (-24.63)	-0.000 (-0.05)	0.026 (0.16)	-0.003* (-1.93)	0.248*** (2.86)
CF	-0.016 (-1.07)	0.000 (1.07)	0.145*** (7.94)	0.001*** (5.29)	0.143*** (3.16)	0.000 (0.66)	-0.009 (-0.68)
CF_sd	-0.200*** (-4.55)	-0.000* (-1.78)	-0.017 (-1.17)	0.000 (0.91)	0.476*** (2.71)	-0.001* (-1.91)	0.005 (0.25)
Nwc	1.254*** (8.99)	-0.000 (-0.61)		-0.000 (-1.31)	0.015 (0.35)	-0.003*** (-6.14)	0.069* (1.77)
Divi			-0.318*** (-7.21)	-0.005*** (-3.28)	-1.205** (-1.96)	0.028*** (3.55)	-2.355** (-2.26)
RD	-13.709***	0.006	0.243	0.002	-1.567	-0.021***	0.713

[37] I use logit regression for the binary dependent variable *Dividend*.

	(-22.99)	(1.61)	(0.71)	(0.61)	(-0.85)	(-3.73)	(0.94)
Capx	-2.952***	-0.018**	-0.840		-8.554	-0.172***	-7.551
	(-6.59)	(-1.99)	(-1.29)		(-0.96)	(-4.94)	(-0.82)
Aqc	-0.376	-0.014***	-0.375**	-0.050***	-0.766	-0.217***	-2.019*
	(-1.29)	(-2.97)	(-2.11)	(-9.48)	(-0.16)	(-6.09)	(-1.78)
Constant	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y
Obs.	21681	21720	21720	21720	16837	20377	20930
adj. R^2	-	0.0479	0.7426	0.2810	0.0014	0.1119	0.0045
Pseudo R^2	0.3454						

4.6 Alternative Explanations

This subsection discusses and rules out competing explanations of increasing cash holdings to further strengthen my main inferences.

4.6.1 The Tax Motive

A potential competing explanation of my results is that my findings may be driven by the U.S. multinational firms that are more likely to retain the earnings in the form of cash in low tax jurisdictions to avoid tax costs related to repatriation (Foley et al., 2007). As such, one may raise a concern that the increase in cash holdings may be ascribed to U.S. multinational firms. To mitigate this concern, I identify U.S. multinational firms using non-missing foreign pretax income and reproduce the regression by excluding multinational firms from my analysis. If my findings are mainly driven by multinational firms, I should not observe any significant relation between CCSN and cash holdings in this subsample. The results in Column 1 of Table 12 suggest that my findings are unlikely to be driven by U.S. multinational firms, ruling out this possible explanation.

4.6.2 The Role of R&D Investments

Another possible explanation is that my results can be explained by firms with higher R&D investments. Bates et al. (2009) document an increasing trend in R&D expenditures during their sample period. Existing research suggests that firms with more R&D investments are more likely to hold cash for precaution purposes (Bates et al., 2009) because R&D investments are less likely to generate assets that can be used as collateral (Pinkowitz et al., 2016). Although my baseline regressions control for R&D expenditures, I exclude firms with R&D expenditures and replicate the analysis to further rule out this alternative explanation. Column 2 of Table 12 presents the estimation results. The results show that my main findings continue to hold for non-R&D-intensive firms, mitigating the concern that my results are driven by R&D-intensive firms.

4.6.3 The Effects of Manufacturing Firms

A third possible explanation is that my results may be driven by technology firms that are more dependent on precautionary cash holdings (Bates et al., 2009). Following Bates et al. (2009), I differentiate technology firms from "old-economy" manufacturing firms that are defined as firms with SIC codes 2000-3999. In this analysis, I focus exclusively on manufacturing firms. The results reported in Column 3 of Table 12 demonstrate that my main findings continue to hold for manufacturing firms, ruling out this alternative explanation.

4.6.4 The Agency Motive

Finally, Jensen (1986) finds that firms with more agency conflicts are more likely to accumulate cash. It is plausible that my findings result from agency problems rather than CCSN. To mitigate this concern, I partition my sample into large and small subsamples based on firm size because prior research suggests that large firms are more likely to have agency problems of free cash flow (Bates et al., 2009).[38] The results reported in the last two columns of Table 12 show that both large and small firms experience an increase in cash holdings due to CCSN. However, compared to large firms, the influence of CCSN on cash holdings is more prominent in small firms, suggesting that the increase in cash holdings is unlikely to be driven by agency problems.

Table 12: Results for Alternative Explanations

Table 12 presents the regression results for ruling out alternative explanations. Column 1 reports the results after excluding U.S. multinational firms. Column 2 reports the results for non-R&D-intensive firms. Column 3 reports the results for old-economy manufacturing firms. Columns 4 and 5 report the results for large and small firms, respectively, based on firm size. Our main explanatory variable is *CCSN*. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1	2	3	4	5
	non-Multinational Firms	non-R&D - intensive firms	Old-economy firms	Large firms	Small firms
CCSN	**0.049*** (6.21)**	**0.015*** (3.25)**	**0.060*** (7.30)**	**0.015*** (5.56)**	**0.059*** (7.12)**
Size	0.042*** (5.73)	-0.027*** (-6.72)	0.022*** (3.66)	-0.030*** (-8.20)	0.112*** (11.43)
MTB	0.019*** (3.53)	0.003 (0.55)	0.016*** (2.99)	0.059*** (14.16)	0.025*** (5.09)
Lev	-0.027*** (-2.88)	-0.018* (-1.91)	-0.071*** (-3.99)	-0.215*** (-8.50)	-0.023** (-2.53)
CF	-0.050*** (-20.76)	-0.041*** (-12.67)	-0.057*** (-17.36)	-0.142*** (-6.68)	-0.054*** (-23.94)
CF_sd	0.017*** (6.04)	0.009*** (2.70)	0.023*** (6.05)	0.062*** (4.11)	0.018*** (6.89)
Nwc	0.038*** (11.74)	0.035*** (8.26)	0.042*** (7.24)	-0.301*** (-7.20)	0.035*** (10.53)
Divi	-0.141*** (-5.70)	0.032*** (2.74)	-0.270*** (-9.82)	-0.038*** (-4.89)	-0.143*** (-4.98)
RD	-0.162*** (-3.05)	-	-0.103* (-1.84)	1.059*** (7.20)	-0.142*** (-3.13)
Capx	-1.141***	-0.444***	-2.770***	-0.657***	-1.681***

[38] Prior literature employs other types of measures of agency problems including the index proposed by Gompers, Ishii, and Metric (2003). However, the data is restricted between 1990 and 2006.

	(-7.63)	(-4.14)	(-10.91)	(-8.43)	(-9.42)
Aqc	-1.202***	-0.431***	-1.468***	-0.447***	-1.781***
	(-11.13)	(-9.99)	(-14.38)	(-13.76)	(-14.96)
Constant	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Obs.	10669	9580	11721	11229	10491
adj. R^2	0.5845	0.3798	0.5854	0.6910	0.5737

4.7 Additional Robustness Tests

I perform several additional robustness checks to validate my main findings. First, I keep data only for the years 2014, 2016, 2018, and 2020 for which the direct climate change opinions data are available from YCOM. Second, following Hilary and Hui (2009), I fill the missing values in the interim years using the linear interpolation method. Third, McGuire et al. (2012) suggest that inter-county commuters may cause county-level measures to have potential measurement errors. I, therefore, re-estimate my model by constructing a state-level measure of CCSN. Fourth, I include state-level fixed effects to control for state-level time-invariant characteristics because climate change adaptation and mitigation policies that may induce CCSN are typically enacted at the state level. Fifth, following Cunha and Pollet (2020), I include industry×year level fixed effects to control for time-varying industry shocks to the firm. Finally, I cluster standard errors at the firm level to eliminate potential serial correlation across firms. The results reported in Table 13 suggest that my main findings continue to hold in all these specifications.

Table 13: Additional Robustness Tests

Table 13 reports the regression results for additional robustness tests. Column 1 reports the results using four years' direct data. Column 2 reports the results when county-level CCSN is calculated using the linear interpolation methodology. Column 3 reports the results based on a state-level CCSN. Column 4 reports the results when state-level fixed effects are controlled for. Column 5 reports the results when industry-times-year level fixed effects are controlled for. Column 6 reports results with standard errors clustered at the firm level. All variables are defined in Appendix A. t-statistics are based on standard errors clustered at the county level (except Column 6). ***, ** and * denote significance at 1%, 5% and 10%, respectively.

	1 Four years' direct data	2 Linear Interpolation	3 S-CCSN	4 State-level fixed effects	5 Industry-times-year fixed effects	6 Standard errors-firm level
CCSN	**0.050***** **(8.32)**	**0.049***** **(8.71)**	**0.049***** **(7.64)**	**0.037***** **(5.18)**	**0.050***** **(8.92)**	**0.050***** **(11.35)**
Size	0.001 (0.28)	0.003 (0.70)	0.005 (1.49)	-0.003 (-0.73)	0.002 (0.66)	0.002 (0.68)
MTB	0.024*** (5.90)	0.023*** (6.05)	0.023*** (6.06)	0.020*** (5.24)	0.022*** (5.80)	0.022*** (5.78)
Lev	-0.048*** (-4.21)	-0.049*** (-4.75)	-0.047*** (-4.73)	-0.042*** (-4.41)	-0.047*** (-4.62)	-0.046*** (-4.68)
CF	-0.053*** (-19.87)	-0.053*** (-20.84)	-0.053*** (-20.97)	-0.053*** (-21.42)	-0.053*** (-20.75)	-0.053*** (-22.00)
CF_sd	0.020*** (6.58)	0.019*** (6.86)	0.019*** (6.95)	0.019*** (7.00)	0.019*** (6.75)	0.019*** (6.83)
Nwc	0.044*** (11.26)	0.044*** (12.33)	0.044*** (12.62)	0.045*** (13.31)	0.045*** (12.57)	0.045*** (12.57)
Divi	-0.155*** (-10.01)	-0.153*** (-10.10)	-0.151*** (-10.53)	-0.134*** (-10.03)	-0.152*** (-9.99)	-0.153*** (-12.31)
RD	-0.052 (-0.96)	-0.067 (-1.33)	-0.067 (-1.34)	-0.104** (-2.16)	-0.061 (-1.23)	-0.066 (-1.36)
Capx	-1.295*** (-9.61)	-1.260*** (-9.63)	-1.255*** (-9.61)	-1.223*** (-9.25)	-1.306*** (-9.71)	-1.258*** (-12.03)
Aqc	-1.033*** (-15.66)	-1.041*** (-16.49)	-1.050*** (-16.98)	-1.005*** (-17.09)	-1.073*** (-16.69)	-1.046*** (-22.25)
Constant	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs.	12420	21521	21711	21711	21703	21720
adj. R^2	0.5723	0.5701	0.5648	0.5797	0.5633	0.5665

5.Conclusions

Using data from YCOM over the period 2014-2020, I document a positive association between CCSN and corporate cash holdings. My main finding is robust to a difference-in-differences specification, which facilitates a causal interpretation of the effect between CCSN and cash holdings. In addition, it is also robust to a battery of robustness checks, including an IV approach, alternative measures of both cash holdings and *CCSN*, additional control variables, subsample analyses, and other different model specifications. My cross-sectional analyses show that the positive association between CCSN and cash holdings is more pronounced for firms that are more financially constrained, during years with a heightened level of media coverage of climate uncertainty, and with greater climate risk exposures. I also find the sources of increased cash holdings. Finally, I rule out alternative explanations that may drive my results.

My results have implications for managers, given that they may face a rising cost of capital in the aftermath of natural disasters (Berg and Schrader, 2012). In particular, I extend the precautionary motives framework by providing a social-norms-based explanation, which helps explain the cash holding behaviors under the context of climate change. In addition, my findings are of interest to investors as well. Compared to firms located in low-CCSN counties, firms in high-CCSN counties are more likely to be resilient to negative shocks resulting from climate-induced extreme weather events and thus less likely to forego profitable investment opportunities brought about by climate risk due to cash shortfall. I believe that exploring the effect of CCSN on corporate behaviors will be a fruitful avenue for future research. Future studies may focus on gathering comparable data at the international level in order to better understand the relationship between CCSN and corporate cash policies with varying institutional factors.

References:

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, 95(9-10), 1082-1095.

Almeida, H., Campello, M., & Weisbach, M. S. (2004). The cash flow sensitivity of cash. *The Journal of Finance*, 59(4), 1777-1804.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4), 1593-1636.

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? Only if you believe in it. *The Review of Financial Studies*, 33(3), 1256-1295.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1), 105-159.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., & Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900-2004. *American Economic Review*, 105(5), 247-51.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to? *The Journal of Finance*, 64(5), 1985-2021.

Baumol, W. J. (1952). The transactions demand for cash: An inventory theoretic approach. *The Quarterly Journal of Economics*, 545-556.

Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4), 549-568.

Callen, J. L., & Fang, X. (2015). Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis*, 50(1-2), 169-195.

Chay, J. B., & Suh, J. (2009). Payout policy and cash-flow uncertainty. *Journal of Financial Economics*, 93(1), 88-107.

Chen, Y., Podolski, E. J., Rhee, S. G., & Veeraraghavan, M. (2014). Local gambling preferences and corporate innovative success. *Journal of Financial and Quantitative Analysis*, 49(1), 77-106.

Cialdini, R. B., & Jacobson, R. P. (2021). Influences of social norms on climate change-related behaviors. *Current Opinion in Behavioral Sciences*, 42, 1-8.

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, 58(6), 1015-1026.

Cunha, I., & Pollet, J. (2020). Why do firms hold cash? Evidence from demographic demand shifts. *The Review of Financial Studies*, 33(9), 4102-4138.

Denis, D. J., & Sibilkov, V. (2010). Financial constraints, investment, and the value of cash holdings. *The Review of Financial Studies*, 23(1), 247-269.

Derrien, F., & Kecskés, A. (2013). The real effects of financial shocks: Evidence from exogenous changes in analyst coverage. *The Journal of Finance*, 68(4), 1407-1440.

Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1), 97-121.

Duchin, R., Ozbas, O., & Sensoy, B. A. (2010). Costly external finance, corporate investment, and the subprime mortgage credit crisis. *Journal of Financial Economics*, 97(3), 418-435.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.

Fama, E. F., & French, K. R. (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay? *Journal of Financial Economics,* 60(3), 43.

Faulkender, M. W., Hankins, K. W., & Petersen, M. A. (2019). Understanding the rise in corporate cash: Precautionary savings or foreign taxes. *The Review of Financial Studies*, 32(9), 3299-3334.

Foley, C. F., Hartzell, J. C., Titman, S., & Twite, G. (2007). Why do firms hold so much cash? A tax-based explanation. *Journal of Financial Economics*, 86(3), 579-607.

Frésard, L. (2010). Financial strength and product market behavior: The real effects of corporate cash holdings. *The Journal of Finance*, 65(3), 1097-1122.

Frésard, L., & Salva, C. (2010). The value of excess cash and corporate governance: Evidence from US cross-listings. *Journal of Financial Economics*, 98(2), 359-384.

Goldberg, M., Gustafson, A., Rosenthal, S., Kotcher, J., Maibach, E., & Leiserowitz, A. (2020). For the first time, the Alarmed are now the largest of Global Warming's Six Americas. Yale Program on Climate Change Communication.

Gompers, P., Ishii, J., & Metrick, A. (2003). Corporate governance and equity prices. *The Quarterly Journal of Economics*, 118(1), 107-156.

Hadlock, C. J., & Pierce, J. R. (2010). New evidence on measuring financial constraints: Moving beyond the KZ index. *The Review of Financial Studies*, 23(5), 1909-1940.

Han, Y., Mao, C. X., Tan, H., & Zhang, C. (2020). Distracted Analysts: Evidence from Climatic Disasters. Available at SSRN 3625803.

Hanlon, M., Maydew, E. L., & Saavedra, D. (2017). The taxman cometh: Does tax uncertainty affect corporate cash holdings? *Review of Accounting Studies*, 22(3), 1198-1228.

Harford, J., Klasa, S., & Maxwell, W. F. (2014). Refinancing risk and cash holdings. *The Journal of Finance*, 69(3), 975-1012.

Harford, J., Mansi, S. A., & Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the US. *Journal of Financial Economics*, 87(3), 535-555.

Harries, T. (2012). The anticipated emotional consequences of adaptive behavior—Impacts on the take-up of household flood-protection measures. *Environment and Planning A*, 44(3), 649-668.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America? *Journal of Financial Economics*, 93(3), 455-473.

Holmström, B., & Tirole, J. (1998). Private and public supply of liquidity. *Journal of Political Economy*, 106(1), 1-40.

Howe, P., Mildenberger, M., Marlon, J., & Leiserowitz, A. 2015. Geographic variation in opinions on climate change at state and local scales in the USA. *Nature Climate Change* 5: 596-603.

Hu, H., Lian, Y., & Zhou, W. (2019). Do local protestant values affect corporate cash holdings? *Journal of Business Ethics*, 154(1), 147-166.

Huang, H.H., Kerstein, J., & Wang, C. 2018. The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5): 633-656.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2), 323-329.

Keynes, J. M. (1936). The general theory of employment. *Interest and Money*. Harcourt: New York.

Kumar, A., Page, J. K., & Spalt, O. G. (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics*, 102(3), 671-708.

Labovitz, S., & Hagedorn, R. (1973). Measuring social norms. *Pacific Sociological Review*, 16(3), 283-303.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C. Y., & Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, 5(11), 1014.

Lorenzoni, I., & Pidgeon, N. F. (2006). Public views on climate change: European and USA perspectives. *Climatic Change*, 77(1), 73-95.

Lyandres, E., & Palazzo, B. (2016). Cash holdings, competition, and innovation. *Journal of Financial and Quantitative Analysis*, 51(6), 1823-1861.

Mase, A. S., Gramig, B. M., & Prokopy, L. S. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern US crop farmers. *Climate Risk Management*, 15, 8-17.

McGuire, S. T., Omer, T. C., & Sharp, N. Y. (2012). The impact of religion on financial reporting irregularities. *The Accounting Review*, 87(2), 645-673.

Miller, G. S. (2006). The press as a watchdog for accounting fraud. *Journal of Accounting Research*, 44(5), 1001-1033.

Neef, A., Benge, L., Boruff, B., Pauli, N., Weber, E., & Varea, R. (2018). Climate adaptation strategies in Fiji: The role of social norms and cultural values. *World Development*, 107, 125-137.

Nyborg, K. (2003). The impact of public policy on social and moral norms: Some examples. *Journal of Consumer Policy*, 26(3), 259-277.

O'Connor, R. E., Bard, R. J., & Fisher, A. (1999). Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Analysis*, 19(3), 461-471.

Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics*, 52(1), 3-46.

Pinkowitz, L., Stulz, R. M., & Williamson, R. (2016). Do US firms hold more cash than foreign firms do? *The Review of Financial Studies*, 29(2), 309-348.

Pirinsky, C., & Wang, Q. (2006). Does corporate headquarters location matter for stock returns? *The Journal of Finance*, 61(4), 1991-2015.

Rivis, A., & Sheeran, P. (2003). Descriptive norms as an additional predictor in the theory of planned behaviour: A meta-analysis. *Current Psychology*, 22(3), 218–233.

Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2020). Firm-level climate change exposure.

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal*, 29(6), 569-592.

Shleifer, A., & Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *The Journal of Finance*, *47*(4), 1343-1366.

Spartz, J. T., Su, L. Y. F., Griffin, R., Brossard, D., & Dunwoody, S. (2017). YouTube, social norms and perceived salience of climate change in the American mind. *Environmental Communication*, 11(1), 1-16.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. Identification and Inference for Econometric Models. W. K.A. Donald, ed. New York: Cambridge University Press.

Tobin, J. (1956). The interest-elasticity of transactions demand for cash. *The Review of Economics and Statistics*, 241-247.

Whited, T. M., & Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, 19(2), 531-559.

Young, D. (2021). How social norms and social identification constrain aggressive reporting behavior. *The Accounting Review*, 96(3), 449-478.

Appendix A: Definitions of Variables

Variables	Definitions
Dependent variables	
Cash1	The ratio of cash and marketable securities to total assets.
Cash2	The ratio of cash and marketable securities to net assets, where net assets are defined as the difference between total assets and cash and marketable securities.
Cash3	Natural logarithm of one plus the ratio of cash and marketable securities to net assets.
Independent variables	
CCSN	Climate change social norms, which is constructed based on the percentages of individuals (1) "who think that global warming is happening"; (2) "who think global warming will harm people in the U.S. a moderate amount/a great deal" and (3) "who are somewhat/very worried about global warming?". Our measure of CCSN is derived by using principal component analysis extracting the first principal component.
CCSN5	Scaled quintile rank of CCSN.
S-CCSN	The measure of CCSN constructed at the state level.
Happening	The percentage of respondents "who think that global warming is happening".
HarmUS	The percentage of respondents "who think global warming will harm people in the U.S. a moderate amount/a great deal".
Worried	The percentage of respondents "who are somewhat/very worried about global warming?".
Control variables	
Size	Natural logarithm of total assets.
MTB	Market value of equity divided by book value of equity.
Lev	Long-term debt plus debt in current liabilities, scaled by total assets.
CF	Cash flow from operations scaled by total assets.
CF_sd	The volatility of cash flows, measured as the standard deviation of cash flow over the past four years.
Nwc	The difference between working capital and cash holdings, scaled by total assets.
Divi	An indicator variable equal to one if the firm paid dividends during the year and zero otherwise.
RD	Research and development expenses scaled by total assets, set to zero if the R&D expenditures are missing in Compustat.
Capx	Capital expenditures scaled by total assets.
Aqc	Acquisition expenses scaled by total assets.
Post	An indicator variable equal to one in the years 2018-2020 and zero in the years 2014-2016.
Neighbor	An indicator variable equal to one if the firm is headquartered in the neighboring states of a state hit by Hurricanes Harvey or Irma and zero
D(t=-1)	otherwise.
D(t=-2)	An indicator variable equal to one for year 2016 and zero otherwise.
D(t=-3)	An indicator variable equal to one for year 2015 and zero otherwise.
D(t=1)	An indicator variable equal to one for year 2014 and zero otherwise.
D(t=2)	An indicator variable equal to one for year 2018 and zero otherwise.
D(t=3)	An indicator variable equal to one for year 2019 and zero otherwise.
Repubpp	An indicator variable equal to one for year 2020 and zero otherwise.
	The percentage of individuals in a ZIP code voting for a Republican Party
CAP	candidate.
	An indicator variable equal to one if a state has CAPs in place or in the process
AvgCCSN	of designing one and zero otherwise.
WW	Average county-level CCSN within a state (excluding the focal county).
	An indicator variable equal to one if the firm's WW index is above the sample median and zero otherwise. Whited and Wu (WW) (2006) index is calculated as: 0.091CF-0.062DIVPOS + 0.021TLTD-0.044LNTA+ 0.102ISG- 0.035SG,

	where CF is cash flow scaled by total assets, DIVPOS is a dummy variable which equals one if the firm pays dividends, TLTD is total long-term debt divided by total assets, LNTA is the natural logarithm of total assets, ISG is average industry sales growth at the 3 digit SIC level and SG is the change of sales per year.
HP	An indicator variable equal to one if the firm's HP index is above the sample median and zero otherwise. Hadlock and Pierce (HP) (2010) index is calculated as: -0.737SIZE + 0.043*SIZE^2 -0.040AGE. where SIZE is natural logarithm of total assets, and AGE is the number of years the firm has been listed on Compustat.
Media	An indicator variable equal to one if the media coverage of climate uncertainty is greater than the sample median and zero otherwise. Media coverage is calculated as the frequency of articles containing the following duo of terms: "climate change" or "global warming" and "uncertain" or "uncertainty" using *The Wall Street Journal*.
Expo	An indicator variable equal to one if a firm's climate risk exposure is greater than the median during the year and zero otherwise.
Dividend	The amount of dividend payouts, scaled by total assets.
SG	Sales growth.
Repurchase	Stock repurchases, calculated as the purchases of common and preferred stock over last year's net income.
Newfin	New financing, measured as the sum of issuance of long-term debt and sales of new stock, divided by market value of equity.
Lat	The latitude of a county.
Lng	The longitude of a county.
Fepp	The proportion of female population in a county.
GDP	County-level per capita GDP.
College	The percentage of population (age 25 and above) who earned a college degree or higher.
Political	A dummy variable equal to one if a state was won by a Democratic presidential candidate in 2 out of 3 presidential elections in the years of 2008, 2012, and 2016, and zero otherwise.

Chapter 3: Climate Change Social Norms and Accounting Conservatism

1. Introduction

Social norms have been identified as an important factor in determining individuals' behavioral intention towards climate change and related climate change mitigation and adaptation policies (e.g., Grothmann and Patt, 2005; Mase et al., 2017; O'Connor et al., 1999). Prior literature suggests that climate change social norms (CCSN, hereafter) enhance individuals' willingness to implement preparedness measures (Wachinger et al., 2013), energy conservation (Allcott, 2011), and environmental conservation (Cialdini, 2003). Considering corporations are not detached from their surrounding environment, surprisingly, there is little research on whether CCSN influences corporate financial reporting choices.

The purpose of this study is to examine whether county-level CCSN influences corporate financial reporting practices in the form of conditional conservatism (i.e., asymmetric timely loss recognition) in the U.S. Prior studies have documented the influence of social norms on various economic behaviors in both accounting and finance literature (e.g., Dyreng et al., 2012; Hilary and Hui, 2009; Hong and Kacperczyk, 2009; McGuire et al., 2012; Young, 2021). Understanding the impact of CCSN on financial reporting practices is important not only because of the heightened level of climate change risk perception and belief after a series of climate-induced extreme weather events in the U.S. but also the urgent need to meet rising demands on climate-related financial disclosures, as emphasized by the U.S. Securities and Exchange Commission (SEC, 2010, 2021).

I focus on conditional conservatism because it involves accounting estimates (i.e., accrual estimates, sales forecasts) which are subject to managers' discretion that could be influenced by how they perceive and interpret the climate change uncertainty (Ilhan et al., 2021). Moreover, prior literature has documented the role of conditional conservatism in reducing information asymmetry and mitigating managerial opportunism (LaFond and Watts, 2008). Given the heightened level of information asymmetry between a firm's insiders and outside investors stemming from climate uncertainty (SEC, 2021), I expect that conditional conservatism may play an even more significant role.[39]

I predict that firms located in counties with higher CCSN are likely to exhibit more conditional conservatism. Climate-induced extreme weather events bring about substantial uncertainty, which exacerbates information asymmetry and provides more room for managerial opportunism. Despite of a consensus on anthropogenic climate change (Powell, 2019), approximately one fourth of individuals in the U.S. are still skeptical of climate change (Goldberg et al., 2020). Thus, it is plausible that climate skeptics behave differently from climate believers when responding to climate change (e.g., Akerlof et al., 2013; Schuldt et al., 2011). Investors and other stakeholders in higher CCSN counties are well aware that climate change is likely to exacerbate firms' information environment and widen the information gap between insiders and outsiders (SEC, 2021). Because the current reporting framework does not provide sufficient climate-related financial information which is critical for investors to make economic and financial decisions (SEC, 2021), CCSN motivates investors and other stakeholders to demand more conditional conservatism to mitigate information asymmetry (LaFond and Watts, 2008) and constrain managers' opportunistic behaviors (Watts, 2003). Relative to climate skeptics in lower CCSN counties, managers who are climate believers are more likely to take climate change into

[39] Although conditional conservatism has been excluded from the joint Conceptual Framework of Financial Accounting Standards Board (FASB) and International Accounting Standards Board (IASB) in 2010, its importance has long been highlighted in the extant literature (e.g., García Lara et al., 2016; Watts, 2003).

account in their financial reporting. Based on the above arguments, I predict that managers of firms headquartered in counties with higher CCSN are more likely to engage in conditional conservatism.

Alternatively, it is plausible that managers of firms headquartered in counties with higher CCSN are more likely to take advantage of other disclosure channels to respond to uncertainty (Nagar et al., 2019), given the complementarity between disclosure and recognition (Dhaliwal et al., 2014). In addition, they may also pursue higher CSR engagement to address information asymmetry (Cho et al., 2013) or use it as a symbolic strategy (Marquis et al., 2016), rather than taking a conservative reporting approach which generally leads to deterioration in contracting efficiency (Guay and Verrecchia, 2006). As a result, investors and other stakeholders are less likely to demand conditional conservatism. This viewpoint is also indirectly supported by the move of the SEC towards a switch to reporting neutrality (FASB, 2010) and its more recent emphasis to meet investors' rising demands on material climate-related financial disclosures (SEC, 2010, 2021). Given these opposing arguments, the relationship between CCSN and conditional conservatism is unclear ex-ante and thus an empirical question.

I measure the county-level CCSN in the U.S. using a novel national representative survey data set culled from the Yale Climate Opinion Maps (YCOM, hereafter) for the period 2014-2020.[40] Prior literature (e.g., Cialdini et al., 1990; Labovitz and Hagedorn, 1973; McGuire et al., 2012) suggests that social norms can be assessed based on the social acceptability of specific belief or attitude. Motivated by this strand of literature, my measure of CCSN is constructed based on the estimated percentages of individuals (1) "who think that global warming is happening"; (2) "who think global warming will harm people in the US a moderate amount/a great deal" and (3)

[40] YCOM is a nationally representative survey conducted biennially starting from 2014 on public opinions about global warming.

"who are somewhat/very worried about global warming?".[41] Utilizing these questions, I compute a county-level CCSN index using the principal component analysis extracting the first principal component and employ it as my primary measure of CCSN in my analysis. I capture conditional conservatism using the models proposed by Basu (1997) and Khan and Watts (2009), respectively, both of which have been widely used in the literature.

My main results indicate that firms headquartered in higher CCSN counties exhibit more conditional conservatism. I address the potential concern that my finding is driven by the occurrence of large natural disasters rather than CCSN by separating my sample into two subsamples: affected and unaffected subsamples and investigating the association separately. The rationale behind this test is that firms in the affected subsample may experience greater losses due to large natural disasters, thus influencing the documented evidence. As expected, my main findings continue to hold for both affected and unaffected subsamples.

I next investigate the robustness of my main findings using a battery of identification and robustness tests. First, I further evaluate the relationship between CCSN and conditional conservatism based on a difference-in-differences (DID) research design using the occurrences of hurricanes as a source of plausibly exogenous shock to individuals' propensity to act on climate change. Second, I mitigate the concern that my measure of CCSN picks up geographical variation in other socioeconomic and political variables by controlling for an extensive set of additional variables. Third, my findings are robust in subsamples partitioned based on the implementation of climate change policies, geography, time periods, and political views. Fourth, I show that my results remain robust to a matched sample analysis. Fifth, I demonstrate that my main findings are

[41] Consistent with prior literature (e.g., Benjamin et al., 2017; Lorenzoni et al., 2006), we use climate change and global warming interchangeably. See also https://climate.nasa.gov/resources/global-warming-vs-climate-change/.

robust to an array of additional robustness tests. Sixth, I confirm that my main results are robust to alternative measures of both CCSN and conditional conservatism.

To the extent that firms headquartered in higher CCSN counties are likely to exhibit more conditional conservatism, I expect the positive association between CCSN and conditional conservatism to be weaker for firms in climate-vulnerable industries because firms in these industries are more prepared for potential impact arising from climate change and face more capital market pressure relative to their counterparts in climate-non-vulnerable industries. Consistent with this expectation, cross-sectional analysis indicates that the positive impact of CCSN on conditional conservatism is more pronounced for climate-non-vulnerable industries. Moreover, I explore whether media coverage on climate change motivates managers of firms located in higher CCSN counties to engage in more conditional conservatism. Consistent with influence of media coverage affecting perceptions, I find that the positive association between CCSN and conditional conservatism is more pronounced during times with greater media coverage related to climate change.

In further analysis, I examine the underlying economic channel through which CCSN influences conditional conservatism. Out of precautionary motives, managers of firms located in counties with higher CCSN are more likely to increase cash holdings to deal with financing problems subsequent to the occurrence of natural disasters (Berg and Schrader, 2012). However, holding excessive cash brings about agency problems. Louis et al. (2012) suggest that accounting conservatism can reduce the value destruction effects of cash holdings. To further investigate whether conditional conservatism is driven by increased cash holdings, I examine the impact of CCSN on corporate cash holdings. My finding shows that firms headquartered in higher CCSN counties hold more cash, suggesting that cash holdings serve as a potential channel through which CCSN influences conditional conservatism.

Finally, given that conditional conservatism recognizes losses in a timelier manner than gains and that managers of firms headquartered in counties with higher CCSN also face capital market pressure, I investigate whether managers engage in real earnings management (REM, hereafter). As expected, I document a positive association between CCSN and REM. Further, considering the potential effect of conditional conservatism on REM (García Lara et al., 2020), I deepen my analysis by exploring the interrelationship among CCSN, conditional conservatism, and REM in a single framework by performing a path analysis. The results from path analysis demonstrate a direct impact of CCSN on REM and an indirect impact via conditional conservatism.

My study contributes to the literature in several important ways. First, I contribute to the literature studying the impact of social norms on financial reporting behaviors (e.g., Dyreng et al., 2012; Hilary and Hui, 2009; McGuire et al., 2012; Young, 2021). Departing from prior literature documenting the impact of social norms in terms of religion and gambling attitudes on various corporate behaviors (e.g., Kumar et al., 2011; McGuire et al., 2012), I focus on CCSN, a nascent form of social norms which has received relatively less attention, and examine its impact of conditional conservatism. To the best of my knowledge, I am among the first to study and document the influence of CCSN on financial reporting practices.

Second, I add to the literature on the determinants of conditional conservatism (e.g., Ahmed and Duellman, 2013; García Lara et al., 2009; Khurana and Wang, 2019). For example, García Lara et al. (2009) show that firms with stronger corporate governance exhibit more conditional conservatism. Ahmed and Duellman (2013) find that managerial overconfidence is negatively associated with conditional conservatism. I complement this literature by identifying CCSN as a potential determinant of conditional conservatism.

Third, my study has significant policy implications for introducing climate change disclosures into the reporting framework. My study implicitly responds to the SEC's recent initiative in addressing climate change reporting (SEC, 2021) by suggesting that the provision of climate risk disclosures may constitute a plausible means to reduce investors' reliance on conditional conservatism and avoid the negative consequences of REM. Under the context of climate change, the rulemaking of climate change disclosure may help standard setters accomplish the transition from conservatism to neutrality.

The rest of the paper is structured as follows. Section 2 discusses the background and relevant literature. Sections 3 discusses hypothesis development. Section 4 describes the data and research design. Section 5 presents the empirical results, and Section 6 concludes the study.

2. Background and Related Literature

2.1 Climate Change Social Norms

There is no universally agreed definition for social norms across various academic fields (e.g., Cialdini et al., 1990; Cialdini, 1993; Cialdini and Jacobson, 2021). According to Cialdini and Jacobson (2021), social norms are defined as "the predominant behaviors, attitudes, beliefs, and codes of conduct of a group". Social norms influence how individuals behave in an acceptable way under certain circumstances. As pointed out by Cialdini (1993), social norms are reinforced by making individuals use the social proof heuristic. As for climate change social norms, it comprises a typical belief or opinion of one's important reference group under the climate change context.

According to social norm theory, imitating the majority's behaviors is a well-established heuristic (e.g., Cialdini et al., 1990), and social norms exert significant influences on human behaviors. Prior studies have shown the importance of social norms in influencing human behaviors (e.g., Allcott, 2011; Kormos et al., 2015; Nolan et al., 2008). For example, Nolan et al. (2008) find that residents are more likely to curb energy usage when they are aware of their neighbors taking steps to reduce energy consumption. In a similar vein, Allcott (2011) shows that customers' energy conservation behavior can be affected by comparing their home energy reports to those of their neighbors, indicating social norms being an effective means to achieve climate change intervention. Given the substantial influence of social norms, failing to obey social norms may result in social sanctions. The associated costs are likely to increase with the strength of social norms (Kanagaretnam et al., 2018).

Prior empirical research in accounting and finance has documented the impact of various norms on corporate behaviors (e.g., Dyreng et al., 2012; Hilary and Hui, 2009; Kumar et al., 2011; McGuire et al., 2012). For example, Hilary and Hui (2009) find that firms headquartered in counties with stronger religiosity exhibit lower risk exposures in terms of variances of return on assets (ROA) and equity return but higher ROA. Using religiosity scores, McGuire et al. (2012) suggest that firms located in religious areas are less likely to engage in financial reporting irregularities related to accounting risk, shareholder lawsuits, and accounting restatements.

Additionally, an emerging literature documents the role of climate-related social norms in influencing individuals' behaviors (e.g., Cialdini and Jacobson, 2021; Mase et al., 2017; O'Connor et al., 1999; Steentjes et al., 2017). Public perception of climate change may significantly influence individual's attitude, response, and support towards mitigation and adaptation policies. For example, O'Connor et al. (1999) show that risk perception is a critical element that results in behavioral intentions to address global warming. Using survey data covering nearly 5000 farmers across the Midwestern U.S., Mase et al. (2017) document that farmers' climate change perception has been identified as a critical factor influencing adaptation strategies to address climate change.

2.2 Conditional Conservatism

I focus on conditional conservatism since it is an important accounting practice whose role in the capital market has been highlighted in prior literature.[42] According to Bliss (1924), conditional conservatism is defined as "anticipate no profit, but anticipate all losses". Basu (1997) defines conditional conservatism as a higher degree of verification threshold for gains than for losses. Since Basu (1997), many studies have examined the determinants and consequences of conditional conservatism (e.g., García Lara et al., 2009, 2016; Khurana and Wang, 2019). Prior research finds that conditional conservatism serves as a contracting mechanism (Watts, 2003), improves investment efficiency (García Lara et al., 2016), and constrains accrual-based earnings management (García Lara et al., 2020). Turning to the literature on the determinants of conditional conservatism (e.g., Ahmed and Duellman, 2013; García Lara et al., 2009; Khurana and Wang, 2019), for example, García Lara et al. (2009) document evidence that firms with stronger governance quality exhibit greater conditional conservatism.

In sum, although there is a large and growing literature on conditional conservatism, surprisingly, there is a dearth of knowledge on how social norms and in particular CCSN influence conditional conservatism. I, therefore, aim to fill the void in the literature by focusing on CCSN and investigate its influence on conditional conservatism.

3. Hypothesis Development

[42] Since I focus exclusively on conditional conservatism in this study, I use conditional conservatism and accounting conservatism interchangeably.

I posit that firms headquartered in higher CCSN counties exhibit higher conditional conservatism. Climate-induced events impact the focal firm through both physical risk to real assets and transition risk imposed by regulatory and economic changes, both of which bring about substantial uncertainty (e.g., Ernst & Young, 2016; Financial Stability Board, 2017; Standard & Poor's, 2017). Given that managers typically have superior information than outside investors on firms' future prospects (Healy and Palepu, 2001), it is possible that managers may expropriate wealth from outside investors by taking advantage of this information advantage (Watts, 2003). For example, managers may not terminate a negative present value project in a timely manner to generate short-term cash flows. Because the existing reporting framework does not provide sufficient climate-related financial information to help them understand, evaluate, and price climate risk and opportunity (SEC, 2021), it is plausible that climate believers likely behave differently from climate skeptics in response to climate uncertainty (e.g., Akerlof et al., 2013; Schuldt et al., 2011). Therefore, CCSN will most likely induce investors and other stakeholders to demand more accounting conservatism to mitigate information asymmetry and agency problems in counties with higher CCSN.

Furthermore, climate-induced extreme weather events affect not only the normal operations of the focal firm but also the operations of its upstream and downstream firms along the supply chain, posing an additional layer of difficulty to forecast sales and operating cash flows. Managers of firms headquartered in higher CCSN counties are arguably influenced by CCSN in dealing with accounting estimates and forecasts. Relative to climate skeptics who deem climate change as a hoax, managers who are climate believers are more likely to take climate change into consideration in their financial reporting. Doing so can also help them circumvent litigation risk stemming from accounting overstatements (Chung and Wynn, 2008; Watts, 2003).

Taken together, the above arguments suggest that firms headquartered in counties with higher CCSN are likely to exhibit more conditional conservatism. I, therefore, propose my hypothesis as follows (in alternate form):

H1: Firms headquartered in counties with higher CCSN are likely to exhibit higher conditional conservatism.

Alternatively, it is plausible that managers of firms headquartered in higher CCSN counties engage less in conditional conservatism. Given the complementarity between financial disclosures and conditional conservatism (Dhaliwal et al., 2014), as well as insufficient climate information disclosures required by the current reporting framework (SEC, 2021), it is plausible that investors and other stakeholders in higher CCSN counties are more inclined to demand additional disclosures rather than conditional conservatism. This is because timely recognition of losses and delays in recognizing gains are likely to underestimate income and make earnings less informative (Guay and Verrecchia, 2006), leading to deterioration in contracting efficiency. In addition, managers of firms located in higher CCSN counties are more likely to respond to uncertainty by using financial disclosures (Nagar et al., 2019). It is also plausible that firms may pursue higher CSR engagement to address information asymmetry (Cho et al., 2013) or employ it as a symbolic strategy (Marquis et al., 2016) to gain legitimacy. The above arguments lend some tension to my hypothesis.

4. Data and Methodology

4.1 Measure of CCSN

Following prior research on social norms employing survey data (e.g., Cialdini et al., 1990; Labovitz and Hagedorn, 1973; McGuire et al., 2012), I measure CCSN using climate change opinion survey data from YCOM for the period 2014-2020. The YCOM is a nationally representative survey conducted biennially on public opinions about global warming. It is particularly appropriate for my research as it contains an extensive list of measures of individuals' opinions on climate-change related issues.

Given that CCSN is nascent and multi-dimensional in nature and can be interpreted in multiple ways, there is no singular definition in the literature. Among all the questions included in the YCOM, I identify three questions that better capture the notion of CCSN and appear each year over the sample period.[43] The choice of these questions is primarily based on the extant literature (e.g., Bouman et al., 2020; Leiserowitz et al., 2018). Specifically, CCSN is constructed based on the estimated percentages of individuals (1) "who think that global warming is happening"; (2) "who think global warming will harm people in the US a moderate amount/a great deal" and (3) "who are somewhat/very worried about global warming?". I derive the measure of CCSN by using principal component analysis extracting the first principal component. Thus, a higher value represents higher CCSN, and vice versa.

I construct my measure of county-level CCSN using the YCOM data for the years of 2014, 2016, 2018, and 2020.[44] Thus, I have to fill in the data for the interim years using the CCSN value of the preceding year. For instance, I filled missing data in 2015 using the CCSN values in 2014.[45, 46]

[43] The number of questions in the YCOM varies across years. However, to maximize the sample size, the questions I selected appear in all survey years.
[44] The YCOM was originally created in 2014 and has been updated in 2016, 2018, 2019, and 2020.
[45] Given that managers' social norms are neither directly observable nor public knowledge, I argue that CCSN can capture managers' climate change-related social norms based on existing literature (e.g., Kumar et al., 2011; McGuire et al., 2012). However, there is a caveat regarding this measure because managers located in the same county could have divergent beliefs.
[46] As a robustness test, I also fill in the interim data using the linear interpolation method and the results (untabulated) remain qualitatively unchanged.

4.2 Measure of Conditional Conservatism

I measure conditional conservatism using models proposed by Basu (1997), and Khan and Watts (2009), respectively, both of which have been extensively employed in the literature. Specifically, I use Basu's (1997) model as my primary measure of conditional conservatism and Khan and Watts (1997) as a robustness test. Under conditional conservatism, there is an asymmetric degree of verification for gains and losses. Thus, bad news are incorporated in a timelier manner than good news into earnings. I adopt Basu's (1997) model as follows:

$$E_t = \alpha_0 + \alpha_1 R_t + \alpha_2 D_t + \alpha_3 R_t * D_t + \varepsilon_t \quad (1)$$

where E_t denotes net income before extraordinary items deflated by the lagged market value of equity; R_t is the annual stock returns, measured by compounding monthly returns ending in the last day of fiscal year t; D_t is an indicator variable that equals one if R_t is negative and zero otherwise. ε_t is the error term. The coefficient α_1 measures the timeliness of earnings with regard to good news, whereas the coefficient α_3 measures the incremental timeliness of earnings with regard to bad news. Under conditional conservatism, α_3 is anticipated to be positive and significant.

4.3 Regression Model

To examine the influence of county-level CCSN on conditional conservatism, I follow prior literature and augment equation (1) by incorporating my key variable- CCSN along with other firm-level characteristics which prior studies have identified as determinants of conditional conservatism (e.g., Ahmed and Duellman, 2013; Goh and Li, 2011; Khan and Watts, 2009). In the climate change settings, to mitigate the concern that CCSN picking up the impact of larger natural disasters, I also control for the occurrence of large disasters (i.e., disasters resulting in losses greater than \$ 3 billion). I then estimate the following equation (2) to examine the relationship between CCSN and conditional conservatism:

$$
\begin{aligned}
E_{it} = {} & \beta_0 + \beta_1 R_{it} + \beta_2 D_{it} + \beta_3 CCSN_{it} + \beta_4 R_{it} * D_{it} + \beta_5 R_{it} * CCSN_{it} + \beta_6 D_{it} * CCSN_{it} \\
& + \beta_7 R_{it} * D_{it} * CCSN_{it} + \beta_8 SIZE_{it} + \beta_9 R_{it} * SIZE_{it} + \beta_{10} D_{it} * SIZE_{it} + \beta_{11} R_{it} \\
& * D_{it} * SIZE_{it} + \beta_{12} MTB_{it} + \beta_{13} R_{it} * MTB_{it} + \beta_{14} D_{it} * MTB_{it} + \beta_{15} R_{it} * D_{it} \\
& * MTB_{it} + \beta_{16} LEV_{it} + \beta_{17} R_{it} * LEV_{it} + \beta_{18} D_{it} * LEV_{it} + \beta_{19} R_{it} * D_{it} * LEV_{it} \\
& + \beta_{20} Big4_{it} + \beta_{21} R_{it} * Big4_{it} + \beta_{22} D_{it} * Big4_{it} + \beta_{23} R_{it} * D_{it} * Big4_{it} \\
& + \beta_{24} Lit_{it} + \beta_{25} R_{it} * Lit_{it} + \beta_{26} D_{it} * Lit_{it} + \beta_{27} R_{it} * D_{it} * Lit_{it} \\
& + \beta_{28} Affected_{it} + \beta_{29} R_{it} * Affected_{it} + \beta_{30} D_{it} * Affected_{it} + \beta_{31} R_{it} * D_{it} \\
& * Affected_{it} + \gamma_i + \delta_t + \theta_j + \varepsilon_{it} \quad (2)
\end{aligned}
$$

where i, and t indexes firms, and years, respectively. *CCSN* denotes climate change social norms, measured as the first major principal component of responses to the three selected questions from the YCOM. Following existing literature (e.g., García Lara et al., 2009; Khan and Watts, 2009), I control for an array of determinants of conditional conservatism, including firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*). I control for these variables to ensure that my results are not driven by these well-documented firm-level determinants (Khan and Watts, 2009). Following Dhaliwal et al. (2014), I control for the presence of a Big4 auditor (*Big4*). Furthermore, following Dhaliwal et al. (2014) and Goh and Li (2011), I control for whether the firm belongs to a litigious industry (*Lit*).[47] In addition to addressing omitted variable bias, controlling for the occurrence of large disasters (*Affected*) also allows us to isolate the incremental effect of CCSN on conditional conservatism. Specifically, following Barrot and Sauvagnat (2016), I focus exclusively on major disasters and place two restrictions on the disaster data: (1) the economic damages caused by a disaster exceed the threshold of \$ 3 billion (in 2020 constant US dollar), and (2) the disaster lasts less than 30 days.[48] After this filtering, I am left with a final data set consisting

[47] A firm belongs to a litigious industry if its four-digit SIC falls in 2833–2836 (biotech), 3570–3577 and 7370–7374 (computer), 3600–3674 (electronics), or 5200–5961 (retailing).

[48] Unlike Barrot and Sauvagnat (2016) who choose a threshold of 1 billion US dollars, I choose 3 billion US dollars as the threshold because there is an increasing trend of economic damages caused by natural disasters over the past

of 34 large natural disasters, including hurricanes, floods, severe weather, storms, and tornadoes.[49] I include three sets of fixed effects. I include industry and year fixed effects, denoted by γ_i and δ_t, respectively, to control for time-invariant industry characteristics and to remove macroeconomic shocks. I also include county-level fixed effects (θ_j) to control for time-invariant county-level characteristics. ε_{it} is the error term. Standard errors are clustered by county to account for potential serial correlation (clustering by firm generates similar results). Detailed definitions of each variable are listed in Appendix A.

In equation (2), consistent with Basu (1997), the coefficient β_1 measures the timeliness of earnings with respect to good news, and the coefficient β_4 reflects the incremental timeliness of earnings with respect to bad news. The coefficient β_5 reflects the effects of CCSN on how quickly earnings recognize good news. My coefficient of interest is β_7, which gauges the impact of CCSN on the incremental timeliness with regards to bad news. A positive β_7 would be consistent with H1 and suggests that firms headquartered in counties with higher CCSN are more likely to engage in conditional conservatism.

4.4 Sample

I obtain climate change opinion data from YCOM, financial data and firm headquarters' locations from Compustat, stock price data from the Center for Research in Security Prices (CRSP), analyst data from the Institutional Brokers Estimate System (I/B/E/S), billion-dollar natural disaster data from National Oceanic and Atmospheric Administration (NOAA), and

decades (Eckstein et al., 2021). Untabulated results show that our findings remain qualitatively unchanged when I change the cut-off value from 3 billion to 1 billion dollars.

[49] The name, date, economic damage, and summary for each major disaster can be obtained from https://www.ncdc.noaa.gov/billions/events/US/1980-2021 and available upon request from the authors.

socioeconomic data from the U.S. Census Bureau. Following prior literature (e.g., Coval and Moskowitz, 1999; Hilary and Hui, 2009; Pirinsky and Wang, 2006), I use the firm's headquarters location to identify its county-level CCSN exposure.[50] My sample starts in 2014 because this is the first year when the YCOM data is available and ends in 2020. I match Compustat data with other data (i.e., CCSN, and data from NOAA and U.S. Census Bureau) using the U.S. ZIP Code.

My initial sample consists of 76,072 firm-year observations for all U.S. public firms with financial data from Compustat during 2014-2020. I remove 11,547 duplicates based on six-digit CUSIP and year. I further remove 9,642 firm-year observations with missing values required to calculate conditional conservatism from CRSP. I drop 27,393 firm-year observations from the utility and financial industries (SIC codes 4900-4999, and 6000-6999, respectively) because they are highly regulated relative to other industries. Finally, I exclude 12,304 firm-year observations with insufficient financial accounting data for the baseline regression. My final sample comprises 15,186 firm-year observations for 3,352 distinct firms during the sample period. A detailed sample selection procedure is displayed in Appendix B.

5. Empirical Results

5.1 Descriptive Statistics

Panel A of Table 1 displays the top and bottom 10 counties in the U.S. based on CCSN. Specifically, Bronx, NY, Alameda, CA, and New York, NY are the top three counties with the highest CCSN, while Overton, TN, Sheridan, WY, and Campbell, TN are the bottom three counties

[50] One concern is that Compustat doesn't report firms' historical headquarter locations. However, according to Pirinsky and Wang (2006), less than 3% of firms changed their headquarter locations.

with the lowest CCSN. Untabulated results show that my data exhibits ample variation at both a cross-sectional and a temporal scale.[51]

The summary statistics and Pearson pairwise correlations for the variables used in the main analysis are presented in Panel B and Panel C of Table 1, respectively. Consistent with prior literature (e.g., Dhaliwal et al., 2014), the dependent variable *E* is left-skewed, suggesting that some firms report large accounting losses. The dummy variable *D* has a mean of 0.527, which indicates that 52.7 % of the annual stock returns of my sample are negative. The mean (median) value of *CCSN* is 0.286 (0.352). In particular, the standard deviation of *CCSN* is 1.556, suggesting substantial variation of CCSN across U.S. counties. The means (medians) of *SIZE*, *MTB*, and *LEV* are 6.535(6.642), 3.684(2.374), and 0.245(0.201), comparable to other studies (e.g., Khurana and Wang, 2019).

Turning to Panel C of Table 1, it is interesting to note that *Affected* is negatively associated with *CCSN*. However, it is not counterintuitive because most significant natural disasters took place in counties where there is a significant number of climate skeptics who exhibit lower *CCSN* as outlined in Panel A of Table 1. No correlation coefficients between *CCSN* and other control variables are greater than 0.5, indicating that multicollinearity is not a major concern for my regression model.[52]

Table 1: Descriptive statistics

Panel A: Comparison of the Top and Bottom Counties in the U.S. as Ranked by CCSN

	Top Counties		Bottom Counties
Rank		Rank	
1	Bronx County, NY	51	Overton County, TN
2	Alameda County, CA	50	Sheridan County, WY
3	New York County, NY	49	Campbell County, TN
4	District of Columbia, DC	48	Fayette County, AL

[51] For example, even for a low CCSN county such as Barbour, Alabama, the percentage of individuals who are concerned about climate change has been increasing from roughly 46% in 2014 to 58% in 2020. I find similar results at the state level. For example, the average percentage of individuals in Alabama who are concerned about climate change has been increasing from roughly 46% in 2014 to 56% in 2020.

[52] The only exception here is the correlation between *Size* and *Big4*, which is consistent with prior literature. However, no VIF exceeding 5 mitigates the concern of multicollinearity. To further address the concern, I omit *Big4* and our results continue to hold.

5	San Francisco County, CA	47	Natrona County, WY
6	Suffolk County, MA	46	Burke County, GA
7	Hudson County, NJ	45	Lee County, MS
8	Honolulu County, HI	44	Jennings County, IN
9	Montgomery County, MD	43	Laramie County, WY
10	San Mateo County, CA	42	Cherokee County, AL

Panel B: Summary Statistics of Selected Variables

	N	Mean	Std. Dev.	p25	Median	p75
E	15186	-.109	.438	-.108	.015	.051
R	15186	.007	.481	-.302	-.024	.236
D	15186	.527	.499	0	1	1
CCSN	15186	.286	1.556	-.619	.352	1.388
SIZE	15186	6.535	2.161	5.023	6.642	8.016
MTB	15186	3.684	13.528	1.229	2.374	4.634
LEV	15186	.245	.256	.021	.201	.372
Big4	15186	.694	.461	0	1	1
Lit	15186	.41	.492	0	0	1
Affected	15186	.299	.458	0	0	1

Panel C: Pairwise Correlations

Variables	(E)	(R)	(D)	(CCSN)	(SIZE)	(MTB)	(LEV)	(Big4)	(Lit)	(Affected)
E	1.000									
R	0.273***	1.000								
D	-0.211***	-0.733***	1.000							
CCSN	-0.074***	0.017**	0.006	1.000						
SIZE	0.291***	0.120***	-0.155***	-0.035***	1.000					
MTB	0.044***	0.077***	-0.060***	0.063***	0.012	1.000				
LEV	-0.017**	-0.061***	0.036***	-0.061***	0.312***	-0.069***	1.000			
Big4	0.165***	0.072***	-0.090***	0.025***	0.577***	0.031***	0.186***	1.000		
Lit	-0.065***	0.028***	0.003	0.214***	-0.213***	0.054***	-0.145***	-0.012	1.000	
Affected	-0.014*	-0.063***	0.055***	-0.098***	0.066***	-0.012	0.068***	-0.004	-0.110***	1.000

Panel A reports top and bottom 10 counties in terms of CCSN. Panel B reports descriptive statistics used in the main analysis. Panel C reports Pearson correlations for the variables used in the main analysis. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.2 Main Regression Results

I report the main regression results on the relationship between CCSN and conditional conservatism in Table 2. Column (1) presents regression results for a parsimoniously augmented Basu’s (1997) model by merely including *CCSN*, its two-way interactions with *R* and *D*, and a three-way interaction with *R* and *D.* The coefficient on the three-way interaction term *R*D*CCSN* is positive and statistically significant at the 1% level (coef. = 0.072, t-stat. = 3.24) in Column (1). Following existing literature (e.g., Khan and Watts, 2009), I include additional firm-level controls such as *SIZE, MTB,* and *LEV* in Column (2). Each control variable is added into the equation as a main effect, a two-way interactions with *R* and *D*, respectively, and a three-way interaction with *R* and *D*. The results reported in Column (2) show that the coefficient on the three-way interaction *R*D*CCSN* is still positive and statistically significant at the 1% level (coef. = 0.055, t-stat. = 2.45) even after controlling for key determinants of conditional conservatism. Together, the results reported in both Columns (1) and (2) provide some preliminary support to H1.

Turing to Column (3) which reports my main regression result, I control for additional variables such as the presence of a Big 4 auditor, litigious industry exposure, and the occurrence of billion-dollar natural disasters as well as their two-way and three-way interactions with *R* and *D*. I find that the coefficient on my main variable of interest (*R*D*CCSN*) remains positive and statistically significant at the 1% level (coef. = 0.081, t-stat. = 3.57), suggesting that managers of firms located in counties with higher CCSN engage in greater conditional conservatism. In terms of economic significance, note that the absolute value of the coefficient on *R*D*CCSN* (0.081) is equivalent to the absolute value of the coefficient on *R*D*SIZE* (-0.103), suggesting that the magnitude of the impact of CCSN on conditional conservatism is similar to that of *SIZE*, another widely acknowledged element influencing conditional conservatism.

Consistent with prior literature (e.g., Dhaliwal et al., 2014), I also find that the coefficient on *R*D*SIZE* is negative and significant at the 1% level (coef. = -0.103, t-stat. = -4.43), indicating that firms with greater size are incrementally less conservative. Moreover, consistent with Goh and Li (2011), the coefficient on *R*D*Lit* is significantly negative at the 1% level (coef. = -0.465, t-stat. = -5.53), suggesting that firms in litigious industries are likely to exhibit less timely loss recognition. The adjusted R-square is reasonably high and comparable with those in the prior literature. Overall, across all specifications, I document consistent evidence that firms headquartered in higher CCSN counties exhibit more conditional conservatism, which lends strong support for H1.

Table 2: OLS Regression Results for the Influence of CCSN on Conditional Conservatism

	(1)		(2)		(3)	
	E	t-stat.	E	t-stat.	E	t-stat.
R	0.002	(0.20)	-0.013	(-0.35)	-0.038	(-1.00)
D	0.082***	(9.14)	0.121***	(3.06)	0.145***	(3.40)
CCSN	-0.046***	(-2.75)	-0.052***	(-3.12)	-0.051***	(-3.00)
R*D	0.678***	(14.72)	0.916***	(7.45)	1.259***	(8.80)

R*CCSN	-0.011*	(-1.65)	-0.009	(-1.45)	-0.008	(-1.25)
D*CCSN	0.009*	(1.68)	0.010**	(1.99)	0.013**	(2.27)
R*D*CCSN	**0.072*** **	**(3.24)**	**0.055** **	**(2.45)**	**0.081*** **	**(3.57)**
SIZE			0.051***	(11.27)	0.046***	(10.99)
R*SIZE			0.004	(0.65)	0.005	(0.88)
D*SIZE			-0.010*	(-1.83)	-0.011**	(-1.98)
R*D*SIZE			-0.075***	(-3.52)	-0.103***	(-4.43)
MTB			-0.001**	(-2.11)	-0.000*	(-1.80)
R*MTB			0.001**	(2.51)	0.001**	(2.52)
D*MTB			0.001*	(1.91)	0.001*	(1.77)
R*D*MTB			-0.003	(-1.24)	-0.003	(-1.27)
LEV			-0.086**	(-2.01)	-0.098**	(-2.36)
R*LEV			-0.001	(-0.03)	0.003	(0.06)
D*LEV			0.054	(1.04)	0.050	(0.95)
R*D*LEV			0.298*	(1.94)	0.239	(1.58)
Big4					0.019	(1.13)
R*Big4					-0.003	(-0.14)
D*Big4					-0.023	(-1.00)
R*D*Big4					-0.012	(-0.13)
Lit					-0.044*	(-1.96)
R*Lit					0.025	(1.45)
D*Lit					-0.042**	(-2.02)
R*D*Lit					-0.465***	(-5.53)
Affected					-0.009	(-0.89)
R*Affected					0.032	(1.61)
D*Affected					0.027	(1.35)
R*D*Affected					0.080	(0.98)
Constant	-0.019**	(-2.54)	-0.345***	(-12.39)	-0.303***	(-10.31)
Industry FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County FE	Yes		Yes		Yes	
N	15282		15192		15186	
adj. R2	0.2766		0.3134		0.3218	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

I also examine whether the positive association between CCSN and conditional conservatism is robust to (i) different homogenous subsamples based on the implementation of climate change policies, geographical locations, time periods, and political views, and (ii) a matched sample analysis. In addition, I investigate whether the positive association between CCSN and conditional conservatism is robust to (i) alternative measure of conditional conservatism (proposed by Khan and Watts (2009)) and (ii) alternative measures of CCSN (e.g., I create a scaled decile rank for the *CCSN* variable). To conserve space, these results are not reported in the paper. Across all specifications, untabulated results show that I consistently document a positive association between CCSN and conditional conservatism.[53]

[53] The results are available from the authors upon request.

5.3 Identification and Robustness Tests

5.3.1 An Alternative Explanation

One potential concern with my main findings is that my results may be driven by the economic damages caused by extreme climate events rather than CCSN. Firms headquartered in counties hit by large disasters are likely to suffer more economic losses and thus exhibit higher accounting conservatism than their counterparts in unaffected counties. Although I have explicitly controlled for the occurrence of large natural disasters in my model, I further mitigate this concern by partitioning my sample into two subsamples: affected and unaffected samples based on the incidence of large natural disasters.

In results reported in Table 3, I continue to document a positive and significant relationship between CCSN and conditional conservatism regardless of the subsample I examine, suggesting that my main finding is not influenced by the occurrence of large natural disasters. Specifically, I find that the coefficients on *R*D*CCSN* remain positive and statistically significant at the 5 % level for affected areas (coef. = 0.058, t-stat. = 2.07) as well as unaffected areas (coef. = 0.096, t-stat. = 2.22). Surprisingly, the coefficient on *R*D*CCSN* is larger for the unaffected sample as compared to that of the affected sample. One possible explanation is that most affected counties are located in low CCSN states, such as the Gulf States including Texas and Louisiana, which are historically susceptible to natural disasters. Overall, since I do not find evidence that the positive association only exists in the affected counties, the evidence documented in this subsection mitigates the potential concern and further validates the positive association between CCSN and conditional conservatism.

Table 3: The Influence of CCSN on Conditional Conservatism: Affected Areas vs Unaffected Areas

	(1) Affected areas E	t-stat.	(2) Unaffected areas E	t-stat.
R	-0.059	(-1.38)	0.001	(0.01)
D	0.123**	(2.27)	0.225***	(2.85)

CCSN	-0.031	(-1.43)	-0.055	(-1.39)
R*D	1.260***	(7.70)	1.666***	(4.87)
R*CCSN	-0.004	(-0.45)	-0.007	(-0.41)
D*CCSN	0.009	(1.33)	0.015	(1.26)
R*D*CCSN	**0.058****	**(2.07)**	**0.096****	**(2.22)**
SIZE	0.042***	(9.34)	0.047***	(5.59)
R*SIZE	0.003	(0.44)	0.014	(1.01)
D*SIZE	-0.006	(-0.87)	-0.022*	(-1.94)
R*D*SIZE	-0.077***	(-2.73)	-0.186***	(-4.10)
MTB	-0.000*	(-1.69)	-0.000	(-0.60)
R*MTB	0.001**	(2.11)	0.001	(0.67)
D*MTB	0.002***	(2.93)	-0.001	(-0.86)
R*D*MTB	0.000	(0.21)	-0.012*	(-1.93)
LEV	-0.144**	(-2.52)	-0.053	(-1.00)
R*LEV	0.044	(0.84)	-0.093	(-0.87)
D*LEV	0.097	(1.37)	0.005	(0.06)
R*D*LEV	0.214	(1.06)	0.286	(1.04)
Big4	0.040**	(2.26)	-0.024	(-0.67)
R*Big4	-0.006	(-0.29)	0.018	(0.33)
D*Big4	-0.061**	(-2.03)	0.046	(1.11)
R*D*Big4	-0.131	(-1.24)	0.241	(1.31)
Lit	-0.041	(-1.63)	-0.038	(-1.04)
R*Lit	0.055***	(2.61)	-0.082**	(-2.01)
D*Lit	-0.026	(-1.00)	-0.118***	(-2.94)
R*D*Lit	-0.499***	(-4.88)	-0.441***	(-2.71)
Constant	-0.275***	(-8.17)	-0.319***	(-5.18)
Industry FE	Yes		Yes	
Year FE	Yes		Yes	
County FE	Yes		Yes	
N	10586		4294	
adj. R2	0.3333		0.2487	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.3.2 Endogeneity Concerns

I now turn my attention to potential endogeneity concerns with my findings and offer some remedies to address them. Even if reverse causality is unlikely to be a concern in my setting because it is unreasonable to expect that conditional conservatism influences CCSN, like most empirical research, my model may suffer from omitted variable bias and measurement errors. In this section, I implement a battery of tests to mitigate these concerns.

5.3.2.1 A Difference-in-Differences Analysis

In this subsection, following prior literature (e.g., Dhaliwal et al., 2014; Khurana and Wang, 2019), I examine the relationship between CCSN and conditional conservatism using a DID research design. Doing so also allows for a causal interpretation of the relationship. Prior literature has documented the impact of large natural disasters on individuals' risk awareness (Dessaint and

Matray, 2017). Consistent with prior studies that document substantial rather than incremental changes in social norms (e.g., Amato et al., 2018; Jones, 2009), I argue that the occurrence of large hurricanes constitutes a source of plausibly exogenous variation in the propensity of individuals to act on climate change. To this end, following prior literature (e.g., Bourveau and Law, 2020), I first identify the occurrence of a series of hurricanes (i.e., Hurricanes Harvey, Irma, and Maria) in 2017 as a plausibly exogenous shock.[54] Specifically, I estimate the following model:

$$\begin{aligned}E_{it} = {} & \beta_0 + \beta_1 R_{it} + \beta_2 D_{it} + \beta_3 R_{it} * D_{it} + \beta_4 Post\ + \beta_5 R_{it} * Strike_{it} + \beta_6 R_{it} * Strike_{it} \\ & * Post\ + \beta_7 D_{it} * Strike_{it} + \beta_8 D_{it} * Strike_{it} * Post + \beta_9 R_{it} * D_{it} * Strike_{it} \\ & + \beta_{10} R_{it} * D_{it} * Strike_{it} * Post + \beta_{11} SIZE_{it} + \beta_{12} R_{it} * SIZE_{it} + \beta_{13} D_{it} \\ & * SIZE_{it} + \beta_{14} R_{it} * D_{it} * SIZE_{it} + \beta_{15} MTB_{it} + \beta_{16} R_{it} * MTB_{it} + \beta_{17} D_{it} \\ & * MTB_{it} + \beta_{18} R_{it} * D_{it} * MTB_{it} + \beta_{19} LEV_{it} + \beta_{20} R_{it} * LEV_{it} + \beta_{21} D_{it} * LEV_{it} \\ & + \beta_{22} R_{it} * D_{it} * LEV_{it} + \beta_{23} Big4_{it} + \beta_{24} R_{it} * Big4_{it} + \beta_{25} D_{it} * Big4_{it} \\ & + \beta_{26} R_{it} * D_{it} * Big4_{it} + \beta_{27} Lit_{it} + \beta_{28} R_{it} * Lit_{it} + \beta_{29} D_{it} * Lit_{it} + \beta_{30} R_{it} \\ & * D_{it} * Lit_{it} + \gamma_i + \delta_t + \theta_j + \varepsilon_{it} \quad (3)\end{aligned}$$

where *Strike* is an indicator variable equal to one if a county where the firm is headquartered is hit by Hurricanes Harvey or Irma in 2017, and zero otherwise; *Post* is an indicator variable equal to one for years after 2017 and zero otherwise. Other variables are defined as previously. My coefficient of interest is the coefficient on the interaction term *R*D*Strike*Post* (β_{10}). It is a difference-in-differences estimate which captures the change in affected firms' conditional conservatism before and after the hurricanes relative to the change in unaffected firms' conditional conservatism. Given the increased influence of CCSN following large disasters, I expect greater conditional conservatism in the post-disaster period for the treated firms as compared to the control firms. All the other variables are as defined previously.[55]

[54] To ensure that the shock is truly exogenous, I require that the states have not been hit by a hurricane in the past three years. Another reason why I focus on these hurricanes is that they caused the most damages during the sample period. Damage caused by Hurricane Harvey is even greater than that of Hurricane Katrina in 2005 and Hurricane Sandy in 2012. In this sense, they are more likely to impact existing social norms on climate change. Since Hurricane Maria didn't hit the U.S. mainland in 2017, I focus only on the other two hurricanes.
[55] The variables of *Strike, R*Post, D*Post,* and *R*D*Post* are subsumed in the regression model and therefore not reported.

I perform a DID test using a propensity score matching (PSM) matched sample based on year, industry, and other control variables used in the main regression to further control for potential heterogeneity of the treated and control firms. I match the firm in the treatment sample with another firm in the control sample using one-on-one nearest neighbor matching without replacement with a caliper of 0.05. As shown in Table 4, the coefficient on *R*D*Strike*Post* is positive and statistically significant at the 1% level (coef. = 0.506, t-stat. = 3.51), suggesting that CCSN heightened by large hurricanes leads to more timely recognition of economic losses for the treated firms relative to the control firms in the post-disaster period.

Table 4: DID Analysis

	(1) E	t-stat.
R	-0.095	(-0.62)
D	0.247*	(1.92)
R*D	1.677***	(3.72)
Post	-0.043	(-0.88)
R*Strike	-0.212*	(-1.88)
R*Strike*Post	0.208*	(1.83)
D*Strike	0.248**	(2.18)
D*Strike*Post	-0.009	(-0.22)
R*D*Strike	0.540	(1.63)
R*D*Strike*Post	**0.506*** **	**(3.51)**
SIZE	0.057***	(3.03)
R*SIZE	0.046*	(1.83)
D*SIZE	-0.027	(-0.77)
R*D*SIZE	-0.288*	(-1.72)
MTB	-0.001	(-1.12)
R*MTB	0.000	(0.22)
D*MTB	0.002	(0.57)
R*D*MTB	-0.007	(-0.48)
LEV	-0.170	(-1.45)
R*LEV	-0.331**	(-2.56)
D*LEV	-0.203	(-1.14)
R*D*LEV	0.288	(0.43)
Big4	-0.206*	(-1.71)
R*Big4	-0.018	(-0.24)
D*Big4	0.174	(0.56)
R*D*Big4	1.531	(1.27)
Lit	-0.179***	(-3.17)
R*Lit	0.042	(0.55)
D*Lit	-0.241	(-1.19)
R*D*Lit	-1.015*	(-1.96)
Constant	-0.116*	(-1.71)
Industry FE	Yes	
Year FE	Yes	
County FE	Yes	
N	3376	
adj. R2	0.1526	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

The DID analysis is based on a key underlying notion: the parallel trends assumption. That is, in the absence of the hurricane shocks, the outcome variables would have parallel trends for both treated and control samples. Following Khurana and Wang (2019), I explore the validity of the parallel trends assumption by including treatment-specific time trends variables (the product of time trend variable and the treatment indicator variable) into my regression model. As reported in Table 5, I continue to document a positive relationship between CCSN and conditional conservatism after controlling for the treatment-specific time trends variables, indicating that my results are unlikely to be affected by preexisting differential trends between the treated and control samples.

Table 5: Parallel Trends Assumption

	(1) E	t-stat.
R	-0.009	(-0.04)
D	0.303**	(2.04)
R*D	1.595**	(2.64)
Post	-0.175	(-1.23)
R*Strike	-0.127	(-1.55)
R*Strike*Post	-0.040	(-0.55)
D*Strike	0.063	(0.88)
D*Strike*Post	-0.127*	(-1.91)
R*D*Strike	-0.125	(-0.76)
R*D*Strike*Post	**0.388****	**(2.50)**
SIZE	0.064**	(2.09)
R*SIZE	0.025	(0.61)
D*SIZE	-0.043	(-1.35)
R*D*SIZE	-0.299	(-1.65)
MTB	-0.001	(-1.34)
R*MTB	0.001	(0.72)
D*MTB	0.001	(0.46)
R*D*MTB	-0.010	(-0.69)
LEV	-0.132	(-1.39)
R*LEV	-0.295*	(-1.84)
D*LEV	-0.197	(-1.00)
R*D*LEV	0.402	(0.58)
Big4	-0.206	(-1.44)
R*Big4	-0.032	(-0.31)
D*Big4	0.227	(0.81)
R*D*Big4	1.745	(1.48)
Lit	-0.164*	(-1.95)
R*Lit	0.022	(0.29)
D*Lit	-0.274	(-1.33)
R*D*Lit	-1.018*	(-1.99)
Constant	-0.125	(-0.89)
Treatment -specific trend	Included	
Treatment -specific trend*R	Included	
Treatment -specific trend*D	Included	
Treatment -specific trend*R*D	Included	
Industry FE	Yes	
Year FE	Yes	
County FE	Yes	
N	3376	
adj. R2	0.1526	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.3.2.2 Additional Robustness Tests

As a robustness test, I control for additional socioeconomic and political variables (such as geographical location, gender, income, educational attainment, and political ideology) to further mitigate the concern of omitted variable bias. In addition, I conduct five more robustness tests using different specifications. These analyses include using (i) four years of direct data on climate change perception, (ii) linear interpolation, (iii) state-level CCSN, (iv) firm-level fixed effects, and

(v) state-level fixed effects. Untabulated results show that my main findings continue to hold in both groups of robustness tests, which further enhance my confidence in my main findings.[56]

5.4 Cross-sectional Analyses

5.4.1 Climate-vulnerable vs Climate-non-vulnerable Industries

Prior studies have documented the differential impact of climate risk on firms' economic decision in different types of industries (e.g., Graff-Zivin and Neidell, 2012; Huang et al., 2018). For example, Huang et al. (2018) find that firms in industries such as agriculture, communication, and transportation are more likely to be negatively affected. They demonstrate that the adverse impacts of climate risk on ROA, earnings volatility, and cash dividends are more pronounced for climate-vulnerable industries.

Earlier research also suggests that physical vulnerability to climate risk is likely to increase perception of climate change. Owusu et al. (2015) find that risk perception is positively associated with protective behaviors. Brody et al. (2008) show that an individual typically has a risk perception regarding sea-level rise if she resides in the vicinity of coasts. Extending this logic to a corporate setting, it is thus plausible that managers of firms in the climate-sensitive industries are more likely to proactively cope with potential extreme weather events by becoming more prepared for climatic extreme events based on protective motives or social pressure imposed by investors and other stakeholders. Given that more preparedness could significantly lessen the magnitude of economic losses and the possibility of disruption of normal operations, counteracting parties are therefore less likely to demand more conditional conservatism. Consistent with this view, Burke et al. (2020) show that firms with more CSR engagement exhibit less conditional conservatism.

[56] The results are available from the authors upon request.

I differentiate climate-vulnerable industries from climate-non-vulnerable industries using two different approaches. Following Huang et al. (2018), I first employ the Fama-French 48 industry scheme to classify Agriculture (Fama-French Industry Code 1), Business Service (Code 34), Communication (Code 32), Food Product (Code 2), Energy (Mines (code 28), Coal (Code 29), and Oil (Code 30)), Health (Code 11), and Transportation (Code 40) as climate-vulnerable industries and others as climate non-vulnerable industries. Alternatively, I follow Graff-Zivin and Neidell (2012) and classify Paper and Forest Products (six-digit GICS code 151050), Metals and Mining (GICS code 151040), Construction and Engineering (GICS code 201030), Automobile and Motorcycle Manufacturers (GICS code 251020), Transportation (GICS codes 203010 to 203050), Agriculture (GICS codes 302020 to 302030), and Utilities (GICS codes 551010 to 551050) as heat-sensitive sectors and others as non-heat-sensitive sectors. I then run regressions separately for these two types of industries based on two different classification schemes.

Table 6 reports the regression results. Results reported in Columns (1) and (2) are based on the Fama-French 48 industry scheme framework while those reported in Columns (3) and (4) are based on the Graff-Zivin and Neidell's (2012) classification scheme. For the vulnerable industries, as shown in Columns (1) and (3), I fail to document a positive association between CCSN and conditional conservatism. However, consistent with my prediction, I find that the coefficients on *R*D*CCSN* are positive and significant at the 1% level for non-vulnerable industries in both Column (2) (coef. = 0.109, t-stat. = 4.39) and Column (4) (coef. = 0.074, t-stat. = 3.20), suggesting that the positive relation between CCSN and conditional conservatism is mainly concentrated in non-vulnerable industries.

Table 6: Cross-sectional Regression Results: The Impact of Climate Vulnerability

	(1) Vulnerable	t-stat.	(2) Non-vulnerable	t-stat.	(3) Vulnerable	t-stat.	(4) Non-vulnerable	t-stat.
R	-0.022	(-0.33)	-0.019	(-0.36)	0.124	(0.52)	-0.026	(-0.67)
D	0.254***	(4.20)	0.113**	(2.19)	0.091	(0.59)	0.161***	(3.84)
CCSN	-0.020	(-0.74)	-0.051**	(-2.49)	-0.017	(-0.31)	-0.053***	(-2.97)

R*D	1.619***	(6.51)	0.981***	(5.94)	0.131	(0.22)	1.292***	(8.85)
R*CCSN	-0.010	(-0.81)	-0.010	(-1.20)	-0.024	(-0.98)	-0.007	(-0.92)
D*CCSN	0.003	(0.38)	0.016**	(2.11)	0.001	(0.09)	0.013**	(2.12)
R*D*CCSN	**0.041**	**(1.08)**	**0.109*****	**(4.39)**	**0.109**	**(1.53)**	**0.074*****	**(3.20)**
SIZE	0.042***	(5.80)	0.056***	(10.28)	0.028	(0.95)	0.046***	(10.80)
R*SIZE	-0.001	(-0.16)	0.005	(0.59)	-0.001	(-0.03)	0.004	(0.70)
D*SIZE	-0.027***	(-3.00)	-0.009	(-1.36)	-0.021	(-0.93)	-0.012**	(-2.06)
R*D*SIZE	-0.179***	(-4.66)	-0.082***	(-3.54)	-0.067	(-0.77)	-0.103***	(-4.30)
MTB	-0.001*	(-1.77)	-0.000	(-1.01)	0.000	(0.21)	-0.000*	(-1.71)
R*MTB	0.002**	(2.17)	0.002	(1.39)	0.003	(1.15)	0.001**	(2.42)
D*MTB	-0.001	(-0.54)	0.002***	(2.64)	0.004	(0.72)	0.001*	(1.79)
R*D*MTB	-0.015**	(-2.10)	-0.000	(-0.00)	0.012	(0.51)	-0.003	(-1.23)
LEV	-0.045	(-0.72)	-0.131**	(-2.27)	-0.053	(-0.37)	-0.100**	(-2.33)
R*LEV	-0.070	(-0.83)	0.032	(0.58)	-0.241	(-1.28)	-0.004	(-0.09)
D*LEV	0.005	(0.07)	0.013	(0.20)	0.342*	(1.79)	0.032	(0.60)
R*D*LEV	0.787***	(2.65)	-0.142	(-1.23)	1.341**	(2.15)	0.212	(1.36)
Big4	0.002	(0.05)	0.031	(1.51)	-0.014	(-0.23)	0.018	(1.02)
R*Big4	0.017	(0.39)	-0.015	(-0.61)	-0.060	(-0.82)	-0.003	(-0.14)
D*Big4	0.073*	(1.84)	-0.049*	(-1.67)	-0.008	(-0.13)	-0.023	(-0.96)
R*D*Big4	0.464**	(2.25)	-0.135	(-1.53)	0.238	(0.84)	-0.020	(-0.21)
Lit	-0.041	(-0.89)	-0.038	(-1.04)	0.000	(.)	-0.038*	(-1.70)
R*Lit	-0.004	(-0.10)	0.028	(1.29)	0.143	(1.27)	0.015	(0.86)
D*Lit	-0.118***	(-4.11)	0.006	(0.26)	-0.142	(-1.60)	-0.050**	(-2.42)
R*D*Lit	-0.644***	(-4.47)	-0.238**	(-2.48)	-0.983**	(-2.00)	-0.474***	(-5.49)
Affected	-0.017	(-0.89)	-0.011	(-1.05)	0.009	(0.25)	-0.007	(-0.70)
R*Affected	0.077*	(1.89)	0.014	(0.60)	-0.015	(-0.18)	0.033	(1.62)
D*Affected	0.001	(0.01)	0.043*	(1.79)	0.010	(0.16)	0.022	(1.03)
R*D*Affected	-0.120	(-0.90)	0.196**	(2.04)	0.288	(0.77)	0.063	(0.75)
Constant	-0.276***	(-5.09)	-0.381***	(-9.03)	-0.194	(-0.98)	-0.303***	(-10.09)
Industry FE	Yes		Yes		Yes		Yes	
Year FE	Yes		Yes		Yes		Yes	
County FE	Yes		Yes		Yes		Yes	
N	4705		10441		878		14298	
adj. R2	0.3011		0.3837		0.3166		0.3251	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.4.2 The Moderating Role of Media Coverage

I next explore how media coverage of climate risk moderates the relationship between CCSN and conditional conservatism. Prior literature suggests that media coverage could increase the salience of disaster events (Dessaint and Matray, 2017). Since uncertainty associated with a changing climate can be substantial, I expect that investors may demand more conditional conservatism, especially during times when climate uncertainty becomes more salient, to mitigate potential information asymmetry (LaFond and Watts, 2008). Given the influence of media coverage on individuals' behaviors as documented in the prior literature (e.g., Miller, 2006), I expect that the influence of CCSN on conservatism is more pronounced during times with a heightened level of media coverage of climate uncertainty.

I measure media coverage of climate change using data obtained from Engle et al. (2020).[57] I partition the sample into two subgroups based on the median media coverage of climate risk and regress conditional conservatism on *CCSN* for both subsamples separately. As shown in Table 7, I find that the coefficient on *R*D*CCSN* is positive and significant at the 5% level (coef. = 0.072, t-stat. = 2.47) during years with higher media coverage of climate uncertainty, while it is insignificant during the years with lower media coverage. In line with LaFond and Watts (2008), this finding is consistent with the notion that information asymmetry increases the demand for conditional conservatism when uncertainty is higher.

Table 7: Cross-sectional Regression Results: The Impact of Media Coverage

	(1) High media coverage	t-stat.	(2) Low media coverage	t-stat.
R	-0.050	(-0.95)	-0.020	(-0.26)
D	0.202***	(3.92)	0.055	(0.69)
CCSN	-0.058***	(-2.79)	-0.047	(-1.45)
R*D	1.389***	(7.62)	1.111***	(3.82)
R*CCSN	-0.004	(-0.48)	-0.004	(-0.32)
D*CCSN	0.017**	(2.41)	-0.006	(-0.46)
R*D*CCSN	**0.072****	**(2.47)**	**0.071**	**(1.43)**
SIZE	0.046***	(8.74)	0.043***	(6.62)
R*SIZE	0.001	(0.11)	0.006	(0.56)
D*SIZE	-0.017**	(-2.48)	0.001	(0.06)
R*D*SIZE	-0.107***	(-3.69)	-0.087**	(-2.10)
MTB	-0.001	(-1.35)	-0.000	(-0.32)
R*MTB	0.001*	(1.75)	0.000	(0.49)
D*MTB	0.001	(0.93)	0.002	(1.47)
R*D*MTB	-0.004	(-1.04)	-0.001	(-0.44)
LEV	-0.131**	(-2.00)	-0.051	(-1.01)
R*LEV	0.029	(0.41)	-0.034	(-0.46)
D*LEV	0.079	(1.08)	0.000	(0.01)
R*D*LEV	0.201	(0.86)	0.316	(1.05)
Big4	0.029	(1.44)	0.004	(0.14)
R*Big4	0.009	(0.38)	-0.006	(-0.12)
D*Big4	-0.033	(-1.06)	-0.059	(-1.24)
R*D*Big4	-0.025	(-0.22)	-0.140	(-0.79)
Lit	-0.052*	(-1.88)	-0.034	(-1.12)
R*Lit	0.059**	(2.53)	-0.033	(-0.96)
D*Lit	-0.043*	(-1.70)	-0.020	(-0.48)
R*D*Lit	-0.491***	(-4.45)	-0.416**	(-2.46)
Affected	-0.010	(-0.87)	-0.015	(-0.41)
R*Affected	0.015	(0.63)	0.068	(1.39)

[57] The index was constructed by Engle et al. (2020) using *The Wall Street Journal* during 1984-2017. I thank Professor Giglio for generously sharing the data set. For our analysis, data for 2014-2017 are employed. Given this short time span, the results should be interpreted with caution.

D*Affected	0.012	(0.48)	0.039	(0.69)
R*D*Affected	0.033	(0.35)	0.243	(1.24)
Constant	-0.286***	(-7.34)	-0.288***	(-5.87)
Industry FE	Yes		Yes	
Year FE	Yes		Yes	
County FE	Yes		Yes	
N	9890		5123	
adj. R2	0.2980		0.2651	

The t-statistics are based on standard errors clustered at the county level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.5 Channel Analysis: The Role of Cash Holdings

Prior research suggests that firms have limited access to external financing in the aftermath of natural disasters (e.g., Berg and Schrader, 2012) and that precautionary motives induce managers to increase cash holdings to deal with negative impacts arising from future natural disasters (Dessaint and Matray, 2017). Following this line of reasoning, I expect that managers of firms headquartered in counties with higher CCSN are likely to hold more cash. The elevated level of cash holdings may increase agency conflicts because managers are more likely to engage in opportunistic behaviors at the expense of shareholders (Jensen, 1986). Investors therefore may require more conditional conservatism to deter managers' opportunistic behaviors. Consistent with this view, Louis et al., (2012) suggest that accounting conservatism can reduce the value destruction effects of cash holdings.

To test the conjecture that cash holdings are a potential channel through which CCSN influences conditional conservatism, following prior literature (e.g., Bates et al., 2009; Opler et al., 1999), I explore the impact of CCSN on cash holdings by estimating the following model:

$$Cash_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 SIZE_{it} + \alpha_3 MTB_{it} + \alpha_4 LEV_{it} + \alpha_5 CFO_{it} + \alpha_6 CFO\_sd_{it} + \alpha_7 NWC_{it} + \alpha_8 Dvc_{it} + \alpha_9 R\&D_{it} + \alpha_{10} Capx_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (4)$$

where i, and t are subscripts, denoting firm and year, respectively; the dependent variable is cash holdings (*Cash*), measured as the ratio of cash and cash equivalent to total assets, and *CCSN*, *SIZE*, *MTB*, *LEV*, and *Affected* are as previously defined. Following prior literature (e.g., Bates et al., 2009; Opler et al., 1999), I control for additional variables that are determinants of cash holdings: operating cash flows scaled by total assets (*CFO*), standard deviation of operating cash flows over the past four years (*CFO_sd*), net working capital scaled by total assets (*NWC*), a dividend payout dummy variable equal to one if the firm paid dividends during the year and zero otherwise (*Dvc*), research and development expenses scaled by total assets (*R&D*), and capital expenditure scaled by total assets (*Capx*). I control for industry- and year- level fixed effects, denoted as γ_i and δ_t, respectively. ε_{it} is the error term which is clustered at the firm level. I expect the sign of *CCSN* to be positive if cash holdings are a potential channel through which CCSN influences conditional conservatism.

Table 8 presents the regression results. The finding shows that the coefficient on *CCSN* is positive and significant at the 1% level (coef. = 0.026, t-stat. = 13.44), suggesting that higher *CCSN* induces managers to increase cash holdings. The signs on the control variables are mostly consistent with the prior literature (e.g., Foley et al., 2007; Pinkowitz and Williamson, 2001). I find that the level of cash holdings increases with market-to-book ratio (*MTB*), R&D expenditure (*R&D*), and volatility of cash flows (*CFO_sd*) whereas it decreases with firm size (*SIZE*), cash flows (*CFO*), dividend payout dummy (*Dvc*), leverage (*LEV*) and capital expenditure (*Capx*). In summary, I interpret this result as evidence that cash holdings serve as a potential channel through which CCSN influences conditional conservatism.

Table 8: Channel Analysis-the Role of Cash Holdings

	(1) Cash	t-stat.
CCSN	**0.026*** **	**(13.44)**
SIZE	-0.011***	(-7.38)
MTB	0.001***	(5.16)
LEV	-0.123***	(-11.12)
CFO	-0.012***	(-13.59)
CFO_sd	0.005***	(4.46)
NWC	0.015***	(14.59)
Dvc	-0.053***	(-8.43)
R&D	0.076***	(4.65)
Capx	-0.473***	(-9.69)
Constant	0.350***	(35.20)
Industry FE	Yes	
Year FE	Yes	

N	15477
adj. R2	0.5276

The t-statistics are based on standard errors clustered at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

5.6 Further Analysis on the Consequences

5.6.1 CCSN and Real Earnings Management

Although I find that CCSN are positively related to conditional conservatism, managers of firms in higher CCSN counties also face capital market pressure (for example, to meet or beat earnings expectations). Accordingly, I proceed to explore whether CCSN influences firms' approach to manipulating earnings. Prior research has documented the substitutive relationship between accrual-based earnings management and REM (Zang, 2012) and the increasing trend in REM (Cohen et al., 2008). In the context of climate change, detecting REM is even more challenging because of the increasing discretion offered to management. Motivated by these observations, I therefore focus on the influence of CCSN on REM.[58]

I follow prior literature (e.g., Cohen and Zarowin 2010; Roychowdhury 2006) and construct an aggregate metric for REM based on abnormal cash flows from operations (*Ab_CFO*) and abnormal discretionary expenses (*Ab_DisX*). Specifically, my measure of REM is calculated as the sum of -1* *Ab_CFO* and -1**Ab_DisX*.[59] Thus, a greater value represents a greater level of REM. To estimate the impact of *CCSN* on REM, following prior literature, I estimate the following model:

[58] Untabulated results show that CCSN reduces accrual-based earnings management. This result, combined with the positive relationship between CCSN and REM, is consistent with Zang (2012).

[59] Our results are qualitatively similar when REM is proxied by the sum of abnormal production and abnormal discretionary expenditure.

$$REM_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 Age_{it} + \alpha_3 Noanalyst_{it} + \alpha_4 SIZE_{it} + \alpha_5 MTB_{it} + \alpha_6 LEV_{it} + \alpha_7 Loss_{it} + \alpha_8 ROA_{it} + \alpha_9 Big4_{it} + \alpha_{10} Dacc_{\ it} + \alpha_{11} Affected_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (5)$$

where *REM* represents the aggregate measure of real earnings management, and *CCSN*, *SIZE*, *MTB*, *LEV*, *Big4*, and *Affected* are defined as before. I also control for additional variables that have been identified as determinants of REM in the literature: the age of the firm (*age*), the number of analysts following a firm (*Noanalyst*), returns on assets (*ROA*), a dichotomous loss variable (*Loss*), and discretionary accruals (*Dacc*) constructed based on the model proposed by Kothari et al. (2005). γ_i and δ_t are industry- and year- level fixed effects, respectively. ε_{it} is the error term. If CCSN positively influences REM, the coefficient on *CCSN* is expected to be positive and significant.

Panel A of Table 9 reports the regression results for equation (5). I find that the coefficient on *CCSN* is positive and significant at the 5% level (coef. = 0.157, t-stat. = 2.20), lending support to the notion that CCSN motivates managers of firms in counties with higher CCSN to engage in more REM in response to capital market pressure. Turning to the control variables, the sign and magnitude of control variables are largely consistent with prior literature.

5.6.2 CCSN, Conditional Conservatism, and REM

Having established the positive relationships between CCSN and conditional conservatism and between CCSN and REM, I deepen my analysis by examining the inter-relationship using a combined framework. My investigation is also motivated by prior research indicating a positive association between conditional conservatism and REM. For example, García Lara et al. (2020) show that conditional conservatism may lead to REM. Following existing literature (e.g., DeFond et al., 2016; Pevzner et al., 2015), I perform a path analysis to examine the direct link between CCSN and REM and the indirect link through conditional conservatism. By using a structural equation model, path analysis decomposes the relationship between a source variable (*CCSN*) and an outcome variable (*REM*) into a direct path and an indirect path through a mediating variable (*Conditional conservatism*) in my case. For ease of interpretation, I adopt the firm-level C_score proposed by Khan and Watts (2009). Specifically, I estimate two equations:

$$REM_{it} = \alpha_0 + \alpha_1 CCSN_{it} + \alpha_2 C\_score_{it} + Controls + Fixed\ effects + \varepsilon_{it} \quad (6)$$

$$C\_score_{it} = \beta_0 + \beta_1 CCSN_{it} + Fixed\ effects + \varepsilon_{it} \quad (7)$$

All variables used in the structural equation model are defined as before. In equation (6), the path coefficient α_1 is the magnitude of the direct path from *CCSN* to *REM*, while the indirect path coefficient is the magnitude of $\alpha_2 * \beta_1$.[60] The significance of the indirect path coefficient is calculated using the Sobel (1982) test statistic.

I report my results for the path analysis in Panel B of Table 9. The direct path coefficient between *CCSN* and *REM* [p (*CCSN*, *REM*)] is positive and significant at the 10% level (coef. = 0.157, t-stat. = 1.72), consistent with firms located in higher *CCSN* counties directly increasing earning manipulation through real activities. The path coefficient between *CCSN* and *C_score* [p (*CCSN*, *C_score*)]is positive and significant at the 1% level (coef. = 0.358, t-stat. = 3.73), in line with my finding that firms in higher *CCSN* counties exhibit more conservatism. The path coefficient between conservatism and REM [p (*C_score*, *REM*)] is positive and significant at the 5% level (coef. = 0.021, t-stat. = 2.16), consistent with the notion that firms exhibiting more conditional conservatism engage in more REM to meet earnings targets. The total mediated path for conditional conservatism [p (*CCSN, C_score*) * p (*C_score*, *REM*)] is positive and significant at the 10% level (coef. = 0.008, t-stat. = 1.87).

Table 9: The Influence of CCSN on REM and Path Analysis

Panel A	(1) REM	t-stat.
CCSN	**0.157****	**(2.20)**
Age	-0.001	(-1.04)
Analyst	-0.000	(-0.17)

[60] The path coefficients are the standardized coefficients generated by path analysis automatically.

SIZE	-0.015	(-0.94)
LEV	-0.139*	(-1.80)
MTB	-0.000	(-0.08)
Loss	0.210***	(6.54)
ROA	-0.100*	(-1.66)
Big4	0.058	(1.23)
Dacc	-0.021	(-0.25)
Affected	-0.003	(-0.10)
Constant	0.135	(1.43)
Industry FE	Yes	
Year FE	Yes	
N	11581	
adj. R2	0.1818	

The t-statistics are based on standard errors clustered at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

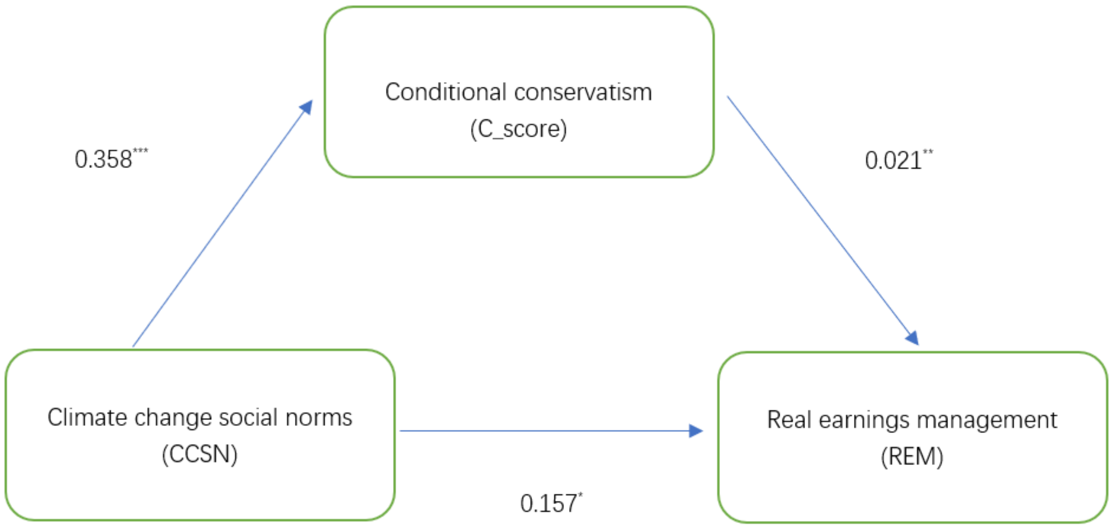
Panel B

Direct path	
p (*CCSN, REM*)	0.157*
	(1.72)
Mediated Path for C_score	
p (*CCSN, C_score*)	0.358***
	(3.73)
p (*C_score, REM*)	0.021**
	(2.16)
Total Mediated Path for conditional conservatism	0.008*
	(1.87)
Controls	Yes
N	10985

The significance of the indirect effect is estimated using the Sobel (1982) test statistics. The t-statistics (reported in parentheses) are based on standard errors clustered at the firm level. ***, **, and * denote significance at 1%, 5%, and 10%, respectively.
Please see Appendix A for variable definitions.

I further graphically illustrate the path analysis results of the direct and indirect effects of *CCSN* on *REM* in Figure 1. In terms of the direct impact, the positive standardized coefficient of 0.157 from *CCSN* to *REM* suggests that a one standard deviation increase in *CCSN* results in a 0.157 standard deviation increase in *REM*. The indirect impact comprises the positive effect of CCSN on conditional conservatism with a standardized path coefficient of 0.358 and the positive effect of conditional conservatism on *REM* with a standardized path coefficient of 0.021. Combining these two paths leads to a positive effect of 0.008 (0.021*0.358), which accounts for and elevates the direct impact by 5.1% (0.008/0.157).

Figure 1: Path Analysis



6. Conclusion

I examine the impact of CCSN on financial accounting practice in the form of conditional conservatism. I find that CCSN is positively related to conditional conservatism. My finding is robust to an extensive array of control variables, different subsamples, and different specifications. Cross-sectional analyses show that the positive relation is more pronounced for climate-non-vulnerable industries and during years with greater media coverage of climate uncertainty. I also document that cash holdings are a potential channel through which CCSN influences conditional conservatism. Finally, using path analysis, my study highlights that CCSN has capital market consequences. That is, it directly influences REM and has indirect influence via conditional conservatism.

I contribute to the literature in several important ways. First, I add to the literature examining the firm-level impact of social norms (e.g., Dyreng et al., 2012; Hilary and Hui, 2009; McGuire et al., 2012; Young, 2021) by showing that CCSN, a nascent form of social norm, influences conditional conservatism. Second, I contribute to a large but growing literature on the determinants of conditional conservatism (e.g., Ahmed and Duellman, 2013; García Lara et al., 2009; Khurana and Wang, 2019) by documenting CCSN as a potential determinant. Third, my study has timely policy implications for a wide range of financial report users, particularly regulators and standard setters who are shaping climate risk disclosures.

Like other empirical studies, my research is subject to certain caveats. My findings are based on the implicit assumption that my proxy precisely captures the CCSN. I acknowledge the challenge in constructing an ideal measure of CCSN, in particular considering that it is multi-dimensional and difficult to measure. However, my consistent findings across a battery of identification and robustness tests to a large extent mitigate this concern and thus expand my understanding of the impact of the CCSN on accounting conservatism. Finally, I do not differentiate the impact of different types of CCSN (descriptive vs. injunctive) and I leave this avenue for future research.

References:

Ahmed, A. S., & Duellman, S. (2013). Managerial overconfidence and accounting conservatism. *Journal of Accounting Research*, 51(1), 1-30.

Akerlof, K., Maibach, E. W., Fitzgerald, D., Cedeno, A. Y., & Neuman, A. (2013). Do people "personally experience" global warming, and if so how, and does it matter? *Global Environmental Change*, 23(1), 81-91.

Allcott, H. (2011). Social norms and energy conservation. *Journal of Public Economics*, 95(9-10), 1082-1095.

Amato, R., Lacasa, L., Díaz-Guilera, A., & Baronchelli, A. (2018). The dynamics of norm change in the cultural evolution of language. *Proceedings of the National Academy of Sciences*, 115(33), 8260-8265.

Basu, S. (1997). The conservatism principle and the asymmetric timeliness of earnings. *Journal of Accounting and Economics*, 24(1), 3-37.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to? *The Journal of Finance*, 64(5), 1985-2021.

Benjamin, D., Por, H. H., & Budescu, D. (2017). Climate change versus global warming: Who is susceptible to the framing of climate change? *Environment and Behavior*, 49(7), 745-770.

Berg, G., & Schrader, J. (2012). Access to credit, natural disasters, and relationship lending. *Journal of Financial Intermediation*, 21(4), 549-568.

Bliss, J. H. (1924). Management through accounts. Ronald Press Company.

Bouman, T., Verschoor, M., Albers, C. J., Böhm, G., Fisher, S. D., Poortinga, W., ... & Steg, L. (2020). When worry about climate change leads to climate action: How values, worry and personal responsibility relate to various climate actions. *Global Environmental Change*, 62, 102061.

Bourveau, T., & Law, K. K. (2021). Do disruptive life events affect how analysts assess risk? Evidence from deadly hurricanes. *The Accounting Review*, 96(3), 121-140.

Brody, S. D., Zahran, S., Vedlitz, A., & Grover, H. (2008). Examining the relationship between physical vulnerability and public perceptions of global climate change in the United States. *Environment and Behavior*, 40(1), 72-95.

Burke, Q. L., Chen, P. C., & Lobo, G. J. (2020). Is Corporate Social Responsibility Performance Related to Conditional Accounting Conservatism? *Accounting Horizons*, 34(2), 19-40.

Cho, S. Y., Lee, C., & Pfeiffer Jr, R. J. (2013). Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy*, 32(1), 71-83.

Chung, H. H., & Wynn, J. P. (2008). Managerial legal liability coverage and earnings conservatism. *Journal of Accounting and Economics*, 46(1), 135-153.

Cialdini, R. B. (1993). The psychology of persuasion. New York.

Cialdini, R. B. (2003). Crafting normative messages to protect the environment. Current Directions in *Psychological Science*, 12(4), 105-109.

Cialdini, R. B., & Jacobson, R. P. (2021). Influences of social norms on climate change-related behaviors. *Current Opinion in Behavioral Sciences*, 42, 1-8.

Cialdini, R. B., Reno, R. R., & Kallgren, C. A. (1990). A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, 58(6), 1015-1026.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. *The Accounting Review*, 83(3), 757-787.

Cohen, D. A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. *Journal of Accounting and Economics*, 50(1), 2-19.

Coval, J. D., & Moskowitz, T. J. (1999). Home bias at home: Local equity preference in domestic portfolios. *The Journal of Finance*, 54(6), 2045-2073.

DeFond, M. L., Lim, C. Y., & Zang, Y. (2016). Client conservatism and auditor-client contracting. *The Accounting Review*, 91(1), 69-98.

Dessaint, O., & Matray, A. (2017). Do managers overreact to salient risks? Evidence from hurricane strikes. *Journal of Financial Economics*, 126(1), 97-121.

Dhaliwal, D., Huang, S., Khurana, I. K., & Pereira, R. (2014). Product market competition and conditional conservatism. *Review of Accounting Studies*, 19(4), 1309-1345.

Dyreng, S. D., Mayew, W. J., & Williams, C. D. (2012). Religious social norms and corporate financial reporting. *Journal of Business Finance & Accounting*, 39(7‐8), 845-875.

Eckstein, D., Künzel, V., & Schäfer, L. (2021). Global climate risk index 2021. Germanwatch, Bonn.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3), 1184-1216.

Ernst & Young. (2016). Climate change. The investment perspective. Available at: https://www.ey.com/Publication/vwLUAssets/EY-climate-change-and-investment/$FILE/EY-climate-change-and-investment.pdf

Financial Accounting Standards Board (FASB) (2010). Statement of Financial Accounting Concepts No.8 Conceptual framework for financial reporting. Norwalk, CT: FAS

Financial Stability Board. (2017). Recommendations of the Task Force on climate-related financial disclosures. Available at: https://www.fsb-tcfd.org/wp-content/uploads/2017/06/FINAL-2017-TCFD-Report-11052018.pdf

Foley, C. F., Hartzell, J. C., Titman, S., & Twite, G. (2007). Why do firms hold so much cash? A tax-based explanation. *Journal of Financial Economics*, 86(3), 579-607

García Lara, J. M., García Osma, B., & Penalva, F. (2009). Accounting conservatism and corporate governance. *Review of Accounting Studies*, 14(1), 161-201.

García Lara, J. M., Garcia Osma, B., & Penalva, F. (2014). Information consequences of accounting conservatism. *European Accounting Review*, 23(2), 173-198.

García Lara, J. M., García Osma, B., & Penalva, F. (2016). Accounting conservatism and firm investment efficiency. *Journal of Accounting and Economics,* 61(1), 221-238.

García Lara, J. M., García Osma, B., & Penalva, F. (2020). Conditional conservatism and the limits to earnings management. *Journal of Accounting and Public Policy*, 39(4), 106738.

Goh, B. W., & Li, D. (2011). Internal controls and conditional conservatism. *The Accounting Review*, 86(3), 975-1005.

Goldberg, M., Gustafson, A., Rosenthal, S., Kotcher, J., Maibach, E., & Leiserowitz, A. (2020). For the first time, the Alarmed are now the largest of Global Warming's Six Americas. Yale Program on Climate Change Communication.

Graff-Zivin, J., & Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review*, 102(7), 3652-73.

Grothmann, T., & Patt, A. (2005). Adaptive capacity and human cognition: the process of individual adaptation to climate change. *Global Environmental Change*, 15(3), 199-213.

Guay, W., & Verrecchia, R. (2006). Discussion of an economic framework for conservative accounting and Bushman and Piotroski (2006). *Journal of Accounting and Economics*, 42(1-2), 149-165.

Healy, P. M., & Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, 31(1-3), 405-440.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America? *Journal of Financial Economics*, 93(3), 455-473.

Hong, H., & Kacperczyk, M. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics*, 93(1), 15-36.

Huang, H. H., Kerstein, J., & Wang, C. (2018). The impact of climate risk on firm performance and financing choices: An international comparison. *Journal of International Business Studies*, 49(5), 633-656.

Ilhan, E., Sautner, Z., & Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3), 1540-1571.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2), 323-329.

Jones, S. (2009). Dynamic social norms and the unexpected transformation of women's higher education, 1965–1975. *Social Science History*, 33(3), 247-291.

Kanagaretnam, K., Lee, J., Lim, C. Y., & Lobo, G. (2018). Societal trust and corporate tax avoidance. *Review of Accounting Studies*, 23(4), 1588-1628.

Khan, M., & Watts, R. L. (2009). Estimation and empirical properties of a firm-year measure of accounting conservatism. *Journal of Accounting and Economics*, 48(2-3), 132-150.

Khurana, I. K., & Wang, W. (2019). International mergers and acquisitions laws, the market for corporate control, and accounting conservatism. *Journal of Accounting Research*, 57(1), 241-290.

Kormos, C., Gifford, R., & Brown, E. (2015). The influence of descriptive social norm information on sustainable transportation behavior: A field experiment. *Environment and Behavior*, 47(5), 479-501.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. *Journal of Accounting and Economics*, 39(1), 163-197.

Kumar, A., Page, J. K., & Spalt, O. G. (2011). Religious beliefs, gambling attitudes, and financial market outcomes. *Journal of Financial Economics*, 102(3), 671-708.

Labovitz, S., & Hagedorn, R. (1973). Measuring social norms. *Pacific Sociological Review*, 16(3), 283-303.

LaFond, R., & Watts, R. L. (2008). The information role of conservatism. *The Accounting Review*, 83(2), 447-478.

Leiserowitz, A., Maibach, E., Roser-Renouf, C., Rosenthal, S., Cutler, M., & Kotcher, J. (2018). Politics & global warming, March 2018. New Haven, CT: Yale University.

Lorenzoni, I., Leiserowitz, A., de Franca Doria, M., Poortinga, W., & Pidgeon, N. F. (2006). Cross-national comparisons of image associations with "global warming" and "climate change" among laypeople in the United States of America and Great Britain. *Journal of Risk Research*, 9(03), 265-281.

Louis, H., Sun, A. X., & Urcan, O. (2012). Value of cash holdings and accounting conservatism. *Contemporary Accounting Research*, 29(4), 1249–1271.

Marquis, C., Toffel, M. W., & Zhou, Y. (2016). Scrutiny, norms, and selective disclosure: A global study of greenwashing. *Organization Science*, 27(2), 483-504.

Mase, A. S., Gramig, B. M., & Prokopy, L. S. (2017). Climate change beliefs, risk perceptions, and adaptation behavior among Midwestern US crop farmers. *Climate Risk Management*, 15, 8-17.

McGuire, S. T., Omer, T. C., & Sharp, N. Y. (2012). The impact of religion on financial reporting irregularities. *The Accounting Review*, 87(2), 645-673.

Miller, G. S. (2006). The press as a watchdog for accounting fraud. *Journal of Accounting Research*, 44(5), 1001-1033.

Nagar, V., Schoenfeld, J., & Wellman, L. (2019). The effect of economic policy uncertainty on investor information asymmetry and management disclosures. *Journal of Accounting and Economics*, 67(1), 36-57.

Nolan, J. M., Schultz, P. W., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2008). Normative social influence is underdetected. *Personality and Social Psychology Bulletin*, 34(7), 913-923.

O'Connor, R. E., Bard, R. J., & Fisher, A. (1999). Risk perceptions, general environmental beliefs, and willingness to address climate change. *Risk Analysis*, 19(3), 461-471.

Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics,* 52(1), 3-46.

Owusu, S., Wright, G., & Arthur, S. (2015). Public attitudes towards flooding and property-level flood protection measures. *Natural Hazards*, 77(3), 1963-1978.

Pevzner, M., Xie, F., & Xin, X. (2015). When firms talk, do investors listen? The role of trust in stock market reactions to corporate earnings announcements. *Journal of Financial Economics*, 117(1), 190-223.

Pinkowitz, L., & Williamson, R. (2001). Bank power and cash holdings: Evidence from Japan. *The Review of Financial Studies,* 14(4), 1059-1082.

Pirinsky, C., & Wang, Q. (2006). Does corporate headquarters location matter for stock returns? *The Journal of Finance*, 61(4), 1991-2015.

Powell, J. (2019). Scientists unanimous on anthropogenic global warming in 2019. *Bulletin of Science, Technology & Society*, 39(1-2), 3-3.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. *Journal of Accounting and Economics*, 42(3), 335–370.

Schuldt, J. P., Konrath, S. H., & Schwarz, N. (2011). “Global warming” or “climate change”? Whether the planet is warming depends on question wording. *Public Opinion Quarterly*, 75(1), 115-124.

SECURITIES AND EXCHANGE COMMISSION (SEC), 2010. Commission Guidance Regarding Disclosure Related to Climate Change [Release Nos. 33-9106; 34-61469; FR-82]. Available at: https://www.sec.gov/rules/interp/2010/33-9106.pdf

SECURITIES AND EXCHANGE COMMISSION (SEC), 2021. Public Input Welcomed on Climate Change Disclosures. Available at: https://www.sec.gov/news/public-statement/lee-climate-change-disclosures.

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, 13, 290-312.

Standard and Poor’s. (2017). How environmental and climate risks and opportunities factor into global corporate ratings - An update. Available at: https://www.spratings.com/documents/20184/1634005/How+Environmental+And+Climate+Risks+And+Opportunities+Factor+Into+Global+Corporate+Ratings+-+An+Update/5119c3fa-7901-4da2-bc90-9ad6e1836801

Steentjes, K., Kurz, T., Barreto, M., & Morton, T. A. (2017). The norms associated with climate change: Understanding social norms through acts of interpersonal activism. *Global Environmental Change*, 43, 116-125.

Wachinger, G., Renn, O., Begg, C., & Kuhlicke, C. (2013). The risk perception paradox—implications for governance and communication of natural hazards. *Risk Analysis*, 33(6), 1049-1065.

Watts, R. L. (2003). Conservatism in accounting part I: Explanations and implications. *Accounting Horizons*, 17(3), 207-221.

Young, D. (2021). How Social Norms and Social Identification Constrain Aggressive Reporting Behavior. *The Accounting Review*, 96(3), 449-478.

Zang, A. Y. (2012). Evidence on the trade-off between real activities manipulation and accrual-based earnings management. *The Accounting Review*, 87(2), 675-703.

Appendix A: Definitions of Variables

Variables	Definitions
Dependent variables	
CAC	Conditional conservatism, which is constructed based on the Basu's (1997) model as follows: $E_t = \alpha_0 + \alpha_1 R_t + \alpha_2 D_t + \alpha_3 R_t * D_t + \varepsilon_t$, where E_t denotes net income before extraordinary items deflated by lagged market value of equity; R_t is the annual buy-and-hold stock return, measured by compounding monthly returns ending the last day of fiscal year t; D_t is an indicator variable that equals one if R_t is negative and zero otherwise. ε_t is the error term.
Independent variables	
CCSN	Climate change social norms, which is constructed based on the percentages of individuals (1) "who think that global warming is happening"; (2) "who think global warming will harm people in the US a moderate amount/a great deal" and (3) "who are somewhat/very worried about global warming?". Our measure of CCSN is derived by using principal component analysis extracting the first principal component.
Happening	Percentage of respondents "who think that global warming is happening".
HarmUS	Percentage of respondents "who think global warming will harm people in the US a moderate amount/a great deal".
Worried	Percentage of respondents "who are somewhat/very worried about global warming?".
Control variables	
SIZE	Natural logarithm of total assets.
MTB	Market value of equity divided by book value of equity.
LEV	Long-term debt scaled by total assets.
Affected	A dummy variable equals one if a major billion-dollar natural disaster occurs in year t in a state, and zero otherwise.
Loss	A dummy variable equal to one if a firm's net income is negative, and zero otherwise.
Big 4	An indicator variable equal to one if the firm is audited by a Big 4 auditor, and zero otherwise.
Lit	An indicator variable for litigious industry, which equals one if a firm's four-digit SIC falls in 2833-2836 (biotech), 3570-3577 and 7370-7374 (computer), 3600-3674 (electronics), or 5200-5961 (retailing), and zero otherwise.
Strike	An indicator variable equal to one if the county where the firm is headquartered is hit by Hurricanes Harvey or Irma in 2017, and zero otherwise.
Post	An indicator variable equal to one for years after 2017 and zero otherwise.
ROA	Return on assets, measured as net income scaled by total assets.
Capx	Capital expenditure divided by total assets.
Dvc	A dummy variable equal to one if the firm paid dividends during the year, and zero otherwise.
R&D	Research and development expenses divided by total assets; missing values are set to zero.
CFO	Cash flow from operations scaled by total assets.
CFO_sd	Standard deviation of cash flows over the past four years.
NWC	Net working capital, measured as the difference between working capital and cash holdings divided by total assets.
Age	Age of the firm, measured as the number of years a firm is listed on Compustat.
Noanalyst	Number of analysts following a firm.
Dacc	Discretionary accruals, calculated using the model proposed by Kothari et al. (2005)
Cash	Ratio of cash and cash equivalent to total assets.
REM	Measure of Real earnings management, which is calculated as the sum of -1* Ab_CFO and -1*Ab_DisX, following Cohen and Zarowin (2010).

Ab_CFO is the abnormal cash flows from operations, which is computed by estimated the following model:

$$\frac{CFO_{it}}{AT_{i,t-1}} = \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{Sales_{it}}{AT_{i,t-1}} + \beta_3 \frac{\Delta Sales_{it}}{AT_{i,t-1}} + \varepsilon_{it}$$

where CFO_{it} is the cash flows from operations of firm i in year t; $AT_{i,t-1}$ is lagged total assets; $Sales_{it}$ is the sales; $\Delta Sales_{it}$ is the changes of sales.

Ab_DisX is the abnormal discretionary expenses, which is computed by estimated the following model:

$$\frac{DisX_{it}}{AT_{i,t-1}} = \beta_1 \frac{1}{AT_{i,t-1}} + \beta_2 \frac{\Delta Sales_{i,t-1}}{AT_{i,t-1}} + \varepsilon_{it}$$

where $DisX_{it}$ is the discretionary expenses of firm i in year t; $AT_{i,t-1}$ is lagged total assets; $\Delta Sales_{i,t-1}$ is the lagged value of $\Delta Sales_{it}$.

Appendix B: Sample Attrition Table

	Number of Observations
Starting with all observation in Compustat over 2014-2020	76,072
Dropping duplicates based on six-digit CUSIP and Year	(11,547)
Merging with CRSP	(9,642)
Dropping firms in regulated industries	(27,393)
Dropping firms with missing variables for baseline regression model	(12,304)
Final sample	15,186