Climate Change Social Norms and Conditional Conservatism

Abstract

Using data from Yale Climate Opinion Maps over the period 2014-2020, we 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 to REM, we perform path analysis and find that CCSN directly influences firms' REM activities and indirectly via conditional conservatism in response to market pressure arising from climate change. Overall, our findings have implications for various financial report users, including standard setters and regulators who are contemplating new climate-related disclosures.

Keywords: Climate change, Social norms, Conditional conservatism, Real earnings management

JEL Classifications: D22, G41, M41, Q54

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 that corporations are not detached from their surrounding environment, as well as that firms operating in different social environments exhibit different behaviors (Christensen et al., 2018; Hasan et al., 2017; Hilary and Hui, 2009; McGuire et al., 2012), 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.[1] 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).

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

We focus on conditional conservatism because its contracting and litigation values (e.g., Basu, 1997; Watts, 2003) are well suited to the climate change context, considering that the IASB conceptual framework reintroduced and defined prudence (conservatism) as "the exercise of caution when making judgements under conditions of uncertainty" (IASB, 2018). Conditional conservatism 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 (e.g., 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), from the perspectives of contracting and litigation, we expect that conditional conservatism may play an even more significant role.[2]

We 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. Following Watts and Zimmerman (1986), we argue that CCSN is a force that determines the demand for and supply of conditional conservatism. On the demand side, investors and other stakeholders in higher CCSN counties demand more conditional conservatism from a

[2] Although conditional conservatism was 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). Realizing the importance of conservatism, the IASB reinstated conservatism in its revised Conceptual Framework in 2018 with a slightly different definition stating "prudence (conservatism) is the exercise of caution when making judgements under conditions of uncertainty" (IASB, 2018).

contracting perspective because they are well aware that climate change is likely to exacerbate moral hazard problems arising from firms' worsened information environment (Kong et al., 2021) and widened information gap between insiders and outsiders (SEC, 2021). Due to the fact that the current reporting framework does not provide sufficient climate-related financial information that could potentially lead to significant proprietary costs, as well as the fact that the disclosed information may increase rather than decrease information asymmetry because it can be manipulated by management (Kolk et al., 2008), CCSN motivates investors and other stakeholders to demand more conditional conservatism to mitigate information asymmetry (Hui et al., 2012; LaFond and Watts, 2008) and constrain managers' opportunistic behaviors (Watts, 2003). On the supply side, relative to climate skeptics in lower CCSN counties, managers who are climate believers are more risk-averse and thus more likely to incorporate bad news quickly due to litigation consideration. Based on the above arguments, we predict that managers of firms headquartered in counties with higher CCSN are more likely to engage in conditional conservatism.

Alternatively, from a valuation perspective, conditional conservatism can be linked to reduced earnings persistence and predictability, as well as enhanced earnings management (Dichev and Tang, 2008). To address these concerns, it is plausible that investors and other stakeholders pressure managers of firms headquartered in counties with higher CCSN to take advantage of other disclosure channels to respond to uncertainty (Nagar et al., 2019), given the potential substitutive relationship between disclosure and conservatism. 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 FASB's switch to reporting neutrality (FASB, 2010) and recent emphasis 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.

Following prior literature (e.g., Christensen et al., 2018; Hilary and Hui, 2009; McGuire et al., 2012), we proxy for managers' CCSN using county-level CCSN in the U.S. based on a novel national representative survey data set culled from the Yale Climate Opinion Maps (YCOM, hereafter) for the period 2014-2020.[3] 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 beliefs or attitudes. Motivated by this strand of literature, our measure of CCSN is constructed based on the estimated percentages of individuals (1) "who think that global warming is happening"; (2) "who think that global warming will harm people in the US a moderate amount/a great deal"; and (3) "who are somewhat/very worried about global warming".[4] Utilizing these questions, we use the first principal component from the principal component analysis to compute a county-level CCSN index, and employ it as our primary measure of CCSN.

Our main results indicate that firms headquartered in higher CCSN counties exhibit more conditional conservatism. We address the potential concern that our finding is driven by the

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

[4] 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/.

occurrence of large natural disasters rather than CCSN by focusing on single-segment firms and separating our sample into 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, our results show that our main findings are not driven by firms in affected counties.

We next investigate the robustness of our main findings using a battery of identification and robustness tests. First, we further evaluate the relationship between CCSN and conditional conservatism based on two difference-in-differences (DID) research designs using the occurrences of hurricanes and the corporate headquarters relocations as a source of plausibly exogenous shock to individuals' propensity to act on climate change. Second, we mitigate the concern that our measure of CCSN picks up geographical variation in other socioeconomic and political variables by controlling for an extensive set of additional variables. Third, our findings are robust in subsamples partitioned based on the implementation of climate change policies, geography, time periods, and political views. Fourth, we show that our results remain robust to a matched sample analysis. Fifth, we demonstrate that our main findings are robust to an array of additional robustness tests. Finally, we confirm that our 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, we 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 the potential impact of 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, we 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, we find that the positive association between CCSN and conditional conservatism is stronger during times with greater media coverage related to climate change.

In further analysis, we 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 challenges subsequent to the occurrence of natural disasters (Berg and Schrader, 2012). However, holding excessive cash brings about agency problems (Jensen, 1986). 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, we examine the impact of CCSN on corporate cash holdings. Our 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, we investigate whether managers engage in real earnings management (REM, hereafter). We focus on REM because Graham et al. (2005) find that managers have strong preferences to use real activities rather than accruals to manipulate reported earnings. As expected, we document a positive association between CCSN and REM. Further, considering the potential effect of conditional conservatism on REM (García Lara et al., 2020), we deepen our analysis by exploring the interrelationship among CCSN, conditional conservatism, and REM in a single framework by performing a path analysis. The results from the path analysis demonstrate a direct impact of CCSN on REM and an indirect impact via conditional conservatism.

Our study contributes to the literature in several important ways. First, we contribute to the literature studying the impact of social norms on corporate behaviors (e.g., Dyreng et al., 2012; Hasan et al., 2017; Hilary and Hui, 2009; McGuire et al., 2012; Young, 2021). Departing from this stream of literature, we focus on CCSN, a nascent form of social norms that has received relatively less attention at the firm level. To the best of our knowledge, we are among the first to study and document the influence of CCSN on financial reporting practices. In particular, we extend and complement the work of Young (2021) by empirically examining the influence of CCSN on financial reporting in terms of conditional conservatism.

Second, we add to the literature on conditional conservatism by responding to the research call of Hanlon et al. (2022) to gain a deeper understanding of the long-term impact of social environment of corporate behaviors. Watts (2003) suggests that conditional conservatism plays a role in reducing the information gap between insiders and outsiders. Further, prior literature also finds that conservatism increases with information asymmetry (Khan and Watts, 2009; LaFond and Watts, 2008). We extend and examine the role of conditional conservatism in a climate change setting, which is typically characterized by a higher level of information asymmetry (SEC, 2021). In this sense, we complement this literature by identifying CCSN as a potential environmental determinant of conditional conservatism.

Third, our study sheds light on the role of CCSN in shaping firms' information environment. As such, this paper has significant policy implications for introducing climate change disclosures in the reporting framework. Our 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.

Like other empirical studies, our research is subject to certain caveats. Our findings are based on the implicit assumption that our proxy precisely captures the CCSN. We acknowledge the challenge in constructing an ideal measure of CCSN, in particular considering that it is multi-dimensional and difficult to measure. However, our consistent findings across a battery of identification and robustness tests to a large extent mitigate this construct validity concern and thus expand our understanding of the impact of the CCSN on accounting conservatism.

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, they comprise 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 that social norms are 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, and 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., Christensen et al., 2018; Dyreng et al., 2012; Hilary and Hui, 2009; 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 individuals' attitudes, responses, 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. Given that corporate behaviors are highly influenced by the surrounding environment (e.g., Hilary and Hui, 2009; McGuire et al., 2012), and that managers are receptive to local attitudes (Christensen et al., 2018), we conjecture that CCSN is likely to influence firms' reporting behaviors.

2.2. Conditional Conservatism

We focus on conditional conservatism because it is an important accounting practice whose role in the capital market has been highlighted in prior literature. 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 (AEM) (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 that firms with stronger governance quality exhibit greater conditional conservatism.

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

3. Hypothesis Development

We posit that firms headquartered in higher CCSN counties exhibit higher conditional conservatism. Following Watts and Zimmerman (1986), we argue that CCSN is a force that determines the demand for and supply of conditional conservatism. On the demand side, we argue that investors and other stakeholders from higher-CCSN counties demand more conditional conservatism to constrain moral hazard problems arising from opaqueness and uncertainty arising from climate change for contracting purposes. 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 by taking advantage of this superior information (Watts, 2003). For example, managers may not terminate a negative net 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 that is typically proprietary to help investors understand, evaluate, and price climate risks and opportunities (SEC, 2021), it is plausible that investors who are climate believers likely behave differently from climate skeptics in response to climate uncertainty (e.g., Akerlof et al., 2013; Schuldt et al., 2011). From a contracting perspective, even if managers may increase information disclosures during periods of uncertainty caused by climate events, investors may still seek more conditional conservatism because information asymmetry arising from uncertainty cannot be fully offset by voluntary disclosures (Nagar et al., 2019).

In addition, other stakeholders, such as debtors, customers, and suppliers, may demand more conditional conservatism from a contracting perspective and use it as a possible mechanism to address moral hazard arising from asymmetric information and asymmetric payoffs (Hui et al., 2012). Against the background of climate change, the classic conflict of interest between shareholders and debtors may become intense, while customers and suppliers are particularly concerned with a firm's ability to fulfill long-term implicit claims and potential switching costs . Therefore, CCSN will most likely induce investors and other stakeholders to demand more accounting conservatism to mitigate information asymmetry and agency problems.

Furthermore, on the supply side, managers may proactively engage in conditional conservatism to avoid potential litigation risks stemming from accounting overstatements. 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 mitigate 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. We, therefore, propose our hypothesis as follows (in alternate form):

Hypothesis 1: Firms headquartered in counties with higher CCSN are likely to exhibit higher conditional conservatism.

Alternatively, from a valuation perspective, conditional conservatism can be linked to reduced earnings persistence and predictability, as well as enhanced earnings management (Dichev and Tang, 2008). Hence, it is plausible that managers of firms headquartered in higher CCSN counties are pressured to engage less in conditional conservatism. Given the substitutive relationship between financial disclosures and conditional conservatism, 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 may 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 are more likely to respond to uncertainty by using financial disclosures (Nagar et al., 2019), in particular for those of firms located in higher CCSN counties. 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 counterarguments lend some tension to our hypothesis.

4. Data and Methodology

4.1. Measure of CCSN

We follow prior literature and argue that county-level CCSN is an ideal proxy capturing managers' view on climate change based on social identity theory.[5] Following prior research on social norms employing survey data (e.g., Cialdini et al., 1990; Labovitz and Hagedorn, 1973; McGuire et al., 2012), we 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 our 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, we identify three questions that better capture the notion of CCSN and appear each year over the sample period.[6] 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 that global warming will harm people in the US a moderate amount/a great deal" and (3) "who are somewhat/very worried about global warming?". We selected these

[5] Prior literature has explored the impact of various social norms on corporate behaviors by utilizing similar constructs on such as religiosity (e.g., Hilary and Hui, 2009; McGuire et al., 2012), social capital (Hasan et al., 2017), and gambling attitudes (Christensen et al., 2018), among others.

[6] The number of questions in the YCOM varies across years. However, the questions we selected appear in all survey years.

three questions from YCOM because they jointly capture the umbrella construct of CCSN. Following prior literature (e.g., Cialdini and Johnson, 2021), CCSN is composed of not only perception but also belief toward climate change. Further, prior literature also highlights the role of worry in the formulation of climate change response (Bouman et al., 2020). Consequently, our measure of CCSN is constructed based on responses to these three questions. We derive the measure of CCSN by using principal component analysis extracting the first principal component from *Happening, HarmUS,* and *Worried*.[7] Thus, a higher value represents higher CCSN, and vice versa.

We construct our measure of county-level CCSN using the YCOM data for the years of 2014, 2016, 2018, and 2020.[8] We fill in the data for the interim years using the CCSN value of the preceding year. For instance, we filled missing data in 2015 using the CCSN values in 2014.[9]

4.2. Measure of Conditional Conservatism

We 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, we use Basu's (1997) model as our 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 is incorporated in a more timely manner than good news into earnings. We adopt Basu's (1997) model as follows:

$$E_{it} = \alpha_0 + \alpha_1 R_{it} + \alpha_2 D_{it} + \alpha_3 R_{it} * D_{it} + \varepsilon_{it} \quad (1)$$

[7] The definitions of these variables are provided in Appendix A.

[8] The YCOM was originally created in 2014 and has been updated in 2016, 2018, 2019, and 2020. Year 2019 data is not available from the YCOM.

[9] As a robustness test, we also fill in the interim data using the linear interpolation method and the results (untabulated) remain qualitatively unchanged.

where E_{it} denotes net income before extraordinary items deflated by the lagged market value of equity; R_{it} is the annual stock returns, measured by compounding monthly returns ending in the last day of fiscal year t; D_{it} is an indicator variable that equals one if R_{it} is negative and zero otherwise. ε_{it} 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.

4.3. Regression Model

To examine the influence of county-level CCSN on conditional conservatism, we follow prior literature and augment equation (1) by incorporating our key variable- CCSN along with other firm-level characteristics that 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, we also control for the occurrence of large disasters (i.e., disasters resulting in losses greater than \$ 3 billion). We then estimate the following equation (2) to examine the relationship between CCSN and conditional conservatism:

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

where i, j, t, and k indexes firms, industries, years, and counties, 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), we control for an array of determinants of conditional conservatism, including firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*). We control for these variables to ensure that our results are not driven by these well-documented firm-level determinants (Khan and Watts, 2009). Following Dhaliwal et al. (2014), we control for the presence of a Big4 auditor (*Big4*). Furthermore, following Dhaliwal et al. (2014) and Goh and Li (2011), we control for whether the firm belongs to a litigious industry (*Lit*).[10] 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), we 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.[11] After this filtering, we are left with a final data set consisting of 34 large natural disasters, including hurricanes, floods, severe weather, storms, and tornadoes.[12] We include a combination of firm, industry, and year fixed effects, denoted by ρ_i, γ_j, and δ_t, respectively, to control for time-invariant firm/industry characteristics and to remove macroeconomic shocks. We 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

[10] 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).

[11] Unlike Barrot and Sauvagnat (2016) who choose a threshold of 1 billion US dollars, we choose 3 billion US dollars as the threshold because there is an increasing trend of economic damages caused by natural disasters over the past decades (Eckstein et al., 2021). Untabulated results show that our findings remain qualitatively unchanged when we change the cut-off value from 3 billion to 1 billion dollars.

[12] 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.

(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. Our 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 that firms headquartered in counties with higher CCSN are more likely to exhibit conditional conservatism.

4.4. Sample

We 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 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), we use the firm's headquarters location to identify its county-level CCSN exposure.[13] Our sample starts in 2014 because this is

[13] Prior literature on "home bias" suggests that investors' preference of local stocks exists not only at an international level but also at a domestic level (e.g., Coval and Moskowitz, 1999). In our main analysis, our results are based on the implicit assumption that home bias is valid at the county level (Coval and Moskowitz, 1999), and the CCSN of investors can be correctly specified accordingly. However, we acknowledge this might be a strong assumption and mitigate this concern by constructing a state-level measure of CCSN. In the robustness test, we find that our main findings continue to hold for state-level measure of CCSN. Another concern is that Compustat doesn't report firms' historical headquarters locations. However, according to Pirinsky and Wang (2006), less than 3% of firms changed their headquarters locations over 1988-2002.

the first year when the YCOM data is available and ends in 2020. We match Compustat data with other data (i.e., CCSN, and data from NOAA and U.S. Census Bureau) using the U.S. ZIP Code.

Our initial sample consists of 76,072 firm-year observations for all U.S. public firms with financial data from Compustat during 2014-2020. We remove 11,547 duplicates based on six-digit CUSIP and year. We further remove 9,642 firm-year observations with missing values required to calculate conditional conservatism from CRSP. We 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, we exclude 12,304 firm-year observations with insufficient financial accounting data for the baseline regression. Our 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 with the lowest CCSN. Untabulated results show that our data exhibits ample variation at both a cross-sectional and a temporal scale.[14]

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

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 our 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 large 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 our regression model.[15]

[Insert Table 1 Here]

5.2. Main Regression Results

We 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

[15] 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, we omit *Big4* and our results continue to hold.

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. = 0.051, t-stat. = 2.60) in Column (1). Following existing literature (e.g., Khan and Watts, 2009), we 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 Columns (3) and (4) which report our main regression results, we 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*. Given that the results are similar under these two slightly different specifications, our discussions focus on Column (4) for the sake of brevity. We find that the coefficient on our main variable of interest (*R*D*CCSN*) remains positive and statistically significant at the 1% level for both models (coef. = 0.081, t-stat. = 3.57), suggesting that managers of firms located in counties with higher CCSN engage in greater conditional conservatism.

Consistent with prior literature (e.g., Dhaliwal et al., 2014), we 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. A possible explanation for this counterintuitive result is that high-tech firms may expense R&D expenditures and this unconditional conservatism preempts conditional conservatism (Beaver and Ryan, 2005). The adjusted R-square is reasonably high and comparable with those in the prior literature. Overall, across all specifications, we document consistent evidence that firms headquartered in higher CCSN counties exhibit more conditional conservatism, which is consistent with H1.

[Insert Table 2 Here]

We 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, we 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., we 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 we consistently document a positive association between CCSN and conditional conservatism.[16]

5.3. Identification and Robustness Tests

5.3.1. An Alternative Explanation

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[16] It is important to note that although Basu's (1997) model has been widely used in the conditional conservatism literature, the usefulness and drawbacks of the model have been hotly debated in prior research, for example, Dietrich et al. (2007), Patatoukas and Thomas (2011, 2016), and Ryan (2006). With this concern in mind, one should exercise certain cautions when interpreting the results. The untabulated results are available from the authors upon request.

One potential concern with our main findings is that our 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. If this is the case, we are more likely to observe a positive relationship between CCSN and conditional conservatism for firms located in affected counties. Although we have explicitly controlled for the occurrence of large natural disasters in our model, we further mitigate this concern by partitioning our sample into: affected and unaffected samples based on the incidence of large natural disasters. In addition, to provide a cleaner identification, we also focus exclusively on single-segment firms with geographic segment data from Compustat.[17]

In results reported in Table 3, we continue to document a positive and significant relationship between CCSN and conditional conservatism for the full sample of single-segment firms. Specifically, we find that the coefficient on *R*D*CCSN* remains positive and statistically significant at the 5% level for the full sample (coef. = 0.094, t-stat. = 2.31). However, the coefficient on *R*D*CCSN* is positive but insignificant for both affected and unaffected subsamples, suggesting that our main finding is not driven by the occurrence of large natural disasters. More importantly, we conduct a t-test to examine the equality of the coefficients on *R*D*CCSN* across affected and unaffected subsamples and the result shows that the difference is not statistically significant at the 10% level. Overall, since we do not find evidence that the positive association only exists in the affected counties, the evidence documented in this subsection mitigates the

[17] We treat a firm as a single-segment firm if Compustat does not have geographic segment data for that firm, otherwise we treat it as a multi-segment firm.

potential concern and further validates the positive association between CCSN and conditional conservatism.

[Insert Table 3 Here]

5.3.2. Endogeneity Concerns

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

5.3.3. A Difference-in-Differences Analysis

In this subsection, following prior literature (e.g., Dhaliwal et al., 2014; Khurana and Wang, 2019), we 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), we 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), we first identify the occurrence of a series of hurricanes (i.e., Hurricanes Harvey, Irma, and Maria) in 2017 as a plausibly exogenous shock.[18] Specifically, we estimate the following model:

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

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. Our 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, we 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.[19]

We 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

[18] To ensure that the shock is truly exogenous, we require that the states have not been hit by a hurricane in the past three years. Another reason why we 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, we focus only on the other two hurricanes.

[19] The variables of *Strike, R*Post, D*Post,* and *R*D*Post* are subsumed in the regression model and therefore not reported.

potential heterogeneity of the treated and control firms. We match each 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 Column (1), 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.

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), we 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 our regression model. As reported in Column (2) of Table 4, we continue to document a positive relationship between CCSN and conditional conservatism after controlling for the treatment-specific time trends variables, indicating that our results are unlikely to be affected by preexisting differential trends between the treated and control samples.

[Insert Table 4 Here]

5.3.4. Further corroborating evidence from firm headquarters relocations

We next provide further corroborating evidence on the positive relationship between CCSN and conditional conservatism by exploiting corporate headquarters relocations. If there is a positive association between CCSN and conditional conservatism, we expect that firms with a CCSN-increasing relocation (i.e., firms that relocate to a county with a higher level of CCSN) should exhibit higher conditional conservatism after relocation. In contrast, firms with a CCSN-decreasing relocation should exhibit lower conditional conservatism.

To test this conjecture, we follow Hasan et al. (2017) and use U.S. SEC 10-K filings to identify corporate headquarters relocations during the sample period. Because our DID analysis requires 3 years' data before and after the relocation events, we restrict our relocation events in 2017 to satisfy this requirement. Thus, we identify 43 relocating firms, including 16 firms with a CCSN-increasing relocation and 27 firms with a CCSN-decreasing relocation in 2017.

We employ a DID model similar to equation (2), except that we replace *Strike* with *CCSN_Increasing_Relocation*, which is an indicator variable equal to one if a firm relocated its headquarters to a county with a higher level of CCSN, and zero if it relocated its headquarters to a county with a lower level of CCSN. *Post* is an indicator variable equal to one for years after 2017 and zero otherwise. We drop all data in the year of relocation, because the level of CCSN changes during that year. The variable of interest in this analysis is the interaction term *R*D*CCSN_Increasing_Relocation*Post*. The standalone effects of *CCSN_Increasing_Relocation* and *Post* are subsumed by fixed effects. As reported in Table 5, the coefficient on *CCSN_Increasing_Relocation* is positive and statistically significant at the 10% level, suggesting that firms with a CCSN-increasing relocation experience an increase in conditional conservatism as opposed to those with a CCSN-decreasing relocation.

Our results will be more convincing if firms with a CCSN-increasing relocation are comparable with those with a CCSN-decreasing relocation in terms of firm characteristics before relocations. Following Hasan et al. (2017), we conduct a group of two-sample t-tests to test whether firm attributes systematically differ across the CCSN-increasing and CCSN-decreasing relocation subsamples prior to the relocation events. Untabulated results show that none of the differences in any dimension of firm attributes are significant at the 5% level, suggesting a reasonable degree of comparability between these two subsamples.[20]

[Insert Table 5 Here]

5.3.5. The incremental role of CCSN to Religion

One potential concern of our study is that the positive association between CCSN and conditional conservatism may be driven by religion. Consistent with this view, Ma et al. (2020) find that firms located in high-religiosity regions exhibit more conditional conservatism. Given that CCSN is likely correlated with religion, we augment equation (2) by controlling for religion and its interactions with R and D. Specifically, following prior literature, we obtain county-level religion data from American Religion Data Archive (ARDA).[21] Untabulated results show that the positive association remains after controlling for religiosity.

5.3.6. Additional Robustness Tests

As an additional robustness test, we control for several 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, we 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) additional sample consisting of both financial and utilities firms, (v) firm-level fixed effects, and

[20] It is important to note that decisions on corporate headquarters relocation could be endogenous (Hasan et al., 2017). Therefore, certain caution should be exercised when interpreting the results.

[21] It is important to note that a disadvantage of this test is that the latest year in which data on religiosity is available from ARDA is 2010.

(vi) state-level fixed effects. Untabulated results show that our main findings continue to hold in both groups of robustness tests, which further enhance our confidence in our main findings.[22]

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. Thus, investors and other stakeholders may demand more conditional conservatism from firms in the climate-vulnerable industries to protect their own interests.

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

[22] Untabulated results are available from the authors upon request.

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.

We differentiate climate-vulnerable industries from climate-non-vulnerable industries using two different approaches. Following Huang et al. (2018), we 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, we 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. We 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), we fail to document a positive association between CCSN and conditional conservatism. However, consistent with our prediction, we 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.

[Insert Table 6 Here]

5.4.2. The Moderating Role of Media Coverage

We 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, we 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), we expect that the influence of CCSN on conservatism is more pronounced during times with a heightened level of media coverage of climate uncertainty.

We measure media coverage of climate change using data obtained from Engle et al. (2020).[23] We 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, we 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

[23] The index was constructed by Engle et al. (2020) using *The Wall Street Journal* during 1984-2017. We 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.

(2008), this finding is consistent with the notion that information asymmetry increases the demand for conditional conservatism when uncertainty is higher.

[Insert Table 7 Here]

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, we 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), we explore the impact of CCSN on cash holdings by estimating the following model:

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

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), we 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*). We control for industry- and year- level fixed effects, denoted as γ_j and δ_t, respectively. ε_{it} is the error term which is clustered at the firm level. We 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. = 4.88), suggesting that higher *CCSN* is associated with higher 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). We 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*), leverage (*LEV*) and capital expenditure (*Capx*). In summary, we interpret this result as evidence that cash holdings serve as a potential channel through which CCSN influences conditional conservatism.

[Insert Table 8 Here]

5.6. Further Analysis on the Consequences

5.6.1. CCSN and Real Earnings Management

Although we 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, we proceed to explore whether CCSN influences firms' approach to manipulating earnings. Prior research has documented the substitutive relationship between AEM and REM (Zang, 2012) and the increasing trend in REM (Cohen et al., 2008). Further, Graham et al. (2005) find that managers have strong preference to use real activities rather than accruals to manipulate reported earnings. In the context of climate change, detecting REM is even more challenging because of the increasing discretion offered to management. Motivated by these observations, we therefore focus on the influence of CCSN on REM.[24]

We 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, our measure of REM is calculated as the sum of -1* *Ab_CFO* and -1**Ab_DisX*.[25] Thus, a greater value represents a greater level of REM. To estimate the impact of *CCSN* on REM, following prior literature, we estimate the following model:

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

where *REM* represents the aggregate measure of real earnings management, and *CCSN*, *SIZE*, *MTB*, *LEV*, *Big4*, and *Affected* are defined as before. We also control for additional variables that have

[24] Untabulated results show that CCSN reduces AEM. This result, combined with the positive relationship between CCSN and REM, is consistent with Zang (2012).

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

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_j 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). We 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, we deepen our analysis by examining the inter-relationship using a combined framework. Our 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), we 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 our case. For ease of interpretation, we adopt the firm-level C_score proposed by Khan and Watts (2009). Specifically, we estimate two equations:

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

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

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 $\alpha_2 * \beta_1$.[26] The significance of the indirect path coefficient is calculated using the Sobel (1982) test statistic.

We report our 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 our 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).

[Insert Table 9 Here]

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

We 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).

[Insert Figure 1 Here]

6. Conclusion

We examine the impact of CCSN on financial accounting practice in the form of conditional conservatism. We find that CCSN is positively related to conditional conservatism. Our 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. We also document that cash holdings are a potential channel through which CCSN influences conditional conservatism. Finally, given the substitution between AEM and REM and managers' preference to REM, we perform path analysis and highlight that CCSN has capital market consequences. That is, CCSN directly influences firms' REM activities and indirectly via conditional conservatism in response to market pressure arising from climate change.

We contribute to the literature in several important ways. First, we 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, we 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, our study has timely policy implications for a wide range of financial report users, particularly regulators and standard setters who are shaping climate risk disclosures.

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Appendix A: Definitions of Variables

Variables	Definitions
Dependent variables	
CAC	Conditional conservatism, which is constructed based on the Basu's (1997) model as follows: $E_{it} = \alpha_0 + \alpha_1 R_{it} + \alpha_2 D_{it} + \alpha_3 R_{it} * D_{it} + \varepsilon_{it}$, where E_{it} denotes net income before extraordinary items deflated by lagged market value of equity; R_{it} is the annual buy-and-hold stock return, measured by compounding monthly returns ending the last day of fiscal year t; D_{it} is an indicator variable that equals one if R_{it} is negative and zero otherwise. ε_{it} 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.
CCSN_Increasing_Relocation	An indicator variable equal to one if a firm relocated its headquarters to a county with a higher level of CCSN, and zero if it relocated its headquarters to a county with a lower level of CCSN.
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

Figure 1: Path Analysis

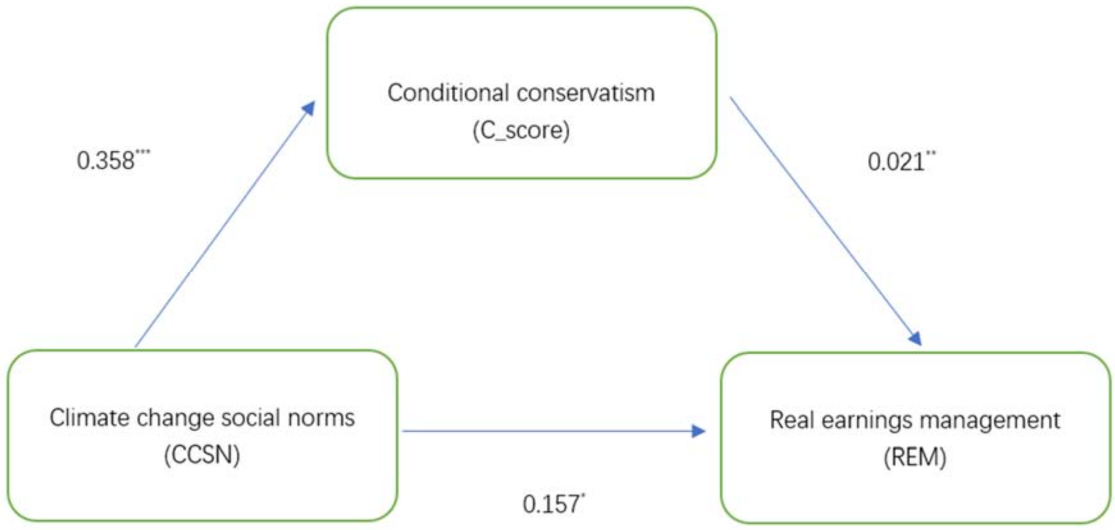

Table 1: Descriptive statistics

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	1461	Overton County, TN
2	Alameda County, CA	1460	Sheridan County, WY
3	New York County, NY	1459	Campbell County, TN
4	District of Columbia, DC	1458	Fayette County, AL
5	San Francisco County, CA	1457	Natrona County, WY
6	Suffolk County, MA	1456	Burke County, GA
7	Hudson County, NJ	1455	Lee County, MS
8	Honolulu County, HI	1454	Jennings County, IN
9	Montgomery County, MD	1453	Laramie County, WY
10	San Mateo County, CA	1452	Cherokee County, AL

Panel B: Summary Statistics of Selected Variables

	N	Mean	Std. Dev.	p25	Median	p75
E	15186	-0.109	0.438	-0.108	0.015	0.051
R	15186	0.007	0.481	-0.302	-0.024	0.236
D	15186	0.527	0.499	0	1	1
CCSN	15186	0.286	1.556	-0.619	0.352	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	0.245	0.256	0.021	0.201	0.372
Big4	15186	0.694	0.461	0	1	1
Lit	15186	0.41	0.492	0	0	1
Affected	15186	0.299	0.458	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.

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

	(1) E	t-stat.	(2) E	t-stat.	(3) E	t-stat.	(4) E	t-stat.
R	0.022**	(2.34)	-0.013	(-0.35)	0.026	(0.76)	-0.038	(-1.00)
D	0.053***	(7.23)	0.121***	(3.06)	0.061*	(1.81)	0.145***	(3.40)
CCSN	-0.041**	(-2.32)	-0.052***	(-3.12)	-0.048***	(-2.68)	-0.051***	(-3.00)
R*D	0.311***	(9.10)	0.916***	(7.45)	0.348***	(2.88)	1.259***	(8.80)
R*CCSN	-0.010*	(-1.68)	-0.009	(-1.45)	-0.011	(-1.53)	-0.008	(-1.25)
D*CCSN	0.005	(1.19)	0.010**	(1.99)	0.006	(1.28)	0.013**	(2.27)
R*D*CCSN	**0.051*** **	**(2.60)**	**0.055** **	**(2.45)**	**0.062*** **	**(3.22)**	**0.081*** **	**(3.57)**
SIZE			0.051***	(11.27)	0.086***	(4.72)	0.046***	(10.99)
R*SIZE			0.004	(0.65)	-0.005	(-0.79)	0.005	(0.88)
D*SIZE			-0.010*	(-1.83)	-0.005	(-1.02)	-0.011**	(-1.98)
R*D*SIZE			-0.075***	(-3.52)	-0.013	(-0.67)	-0.103***	(-4.43)
MTB			-0.001**	(-2.11)	-0.000	(-0.59)	-0.000*	(-1.80)
R*MTB			0.001**	(2.51)	0.000	(0.78)	0.001**	(2.52)
D*MTB			0.001*	(1.91)	0.000	(0.31)	0.001*	(1.77)
R*D*MTB			-0.003	(-1.24)	-0.002	(-1.03)	-0.003	(-1.27)
LEV			-0.086**	(-2.01)	-0.058	(-0.82)	-0.098**	(-2.36)
R*LEV			-0.001	(-0.03)	-0.017	(-0.25)	0.003	(0.06)
D*LEV			0.054	(1.04)	0.027	(0.44)	0.050	(0.95)
R*D*LEV			0.298*	(1.94)	0.207	(1.43)	0.239	(1.58)
Big4					-0.015	(-0.41)	0.019	(1.13)
R*Big4					0.008	(0.36)	-0.003	(-0.14)
D*Big4					-0.005	(-0.21)	-0.023	(-1.00)
R*D*Big4					-0.023	(-0.26)	-0.012	(-0.13)
Lit					0.000	(.)	-0.044*	(-1.96)
R*Lit					0.015	(0.87)	0.025	(1.45)
D*Lit					-0.002	(-0.12)	-0.042**	(-2.02)
R*D*Lit					-0.173**	(-2.52)	-0.465***	(-5.53)
Affected					-0.013	(-1.32)	-0.009	(-0.89)
R*Affected					0.050**	(2.04)	0.032	(1.61)
D*Affected					0.048**	(2.37)	0.027	(1.35)
R*D*Affected					0.125	(1.49)	0.080	(0.98)
Constant	-0.068***	(-10.75)	-0.345***	(-12.39)	-0.602***	(-5.23)	-0.303***	(-10.31)
Firm FE	Yes		No		Yes		No	
Industry FE	No		Yes		No		Yes	
Year FE	Yes		Yes		Yes		Yes	
County FE	Yes		Yes		Yes		Yes	
N	14971		15192		14874		15186	
adj. R2	0.5634		0.3134		0.3830		0.3218	

This table presents the results of the following regression:

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

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.

Table 3: The Influence of CCSN on Conditional Conservatism for single-segment firms: Affected Areas vs Unaffected Areas

	(1) Full sample		(2) Affected areas		(3) Unaffected areas	
	E	t-stat.	E	t-stat.	E	t-stat.
R	0.011	(0.11)	-0.268	(-0.85)	0.096	(0.69)
D	0.025	(0.22)	-0.341	(-1.36)	0.155	(0.97)
CCSN	-0.103**	(-2.15)	-0.208	(-1.23)	-0.028	(-0.63)
R*D	0.187	(0.83)	0.695	(1.21)	0.220	(0.83)
R*CCSN	-0.013	(-0.73)	0.016	(0.35)	-0.005	(-0.21)
D*CCSN	0.017	(1.06)	0.009	(0.24)	0.017	(0.81)
R*D*CCSN	**0.094***	**(2.31)**	**0.061**	**(0.57)**	**0.071**	**(1.45)**
SIZE	0.083***	(5.28)	0.043	(0.91)	0.090***	(5.68)
R*SIZE	0.002	(0.11)	0.063	(1.12)	-0.013	(-0.61)
D*SIZE	0.028*	(1.68)	0.098**	(2.36)	0.003	(0.16)
R*D*SIZE	0.092*	(1.89)	0.036	(0.32)	0.076	(1.50)
MTB	-0.001	(-1.41)	-0.004*	(-1.67)	-0.001	(-0.71)
R*MTB	0.000	(0.39)	0.006	(1.52)	-0.000	(-0.29)
D*MTB	0.002	(1.02)	-0.001	(-0.13)	0.002	(1.31)
R*D*MTB	-0.004	(-0.98)	-0.028**	(-2.27)	0.002	(0.61)
LEV	-0.001	(-0.02)	-0.235	(-1.10)	0.047	(0.54)
R*LEV	-0.049	(-0.70)	0.101	(0.44)	-0.132	(-1.42)
D*LEV	-0.188*	(-1.84)	-0.441	(-1.47)	-0.187*	(-1.69)
R*D*LEV	-0.560*	(-1.96)	-1.312*	(-1.87)	-0.363	(-1.03)
Big4	0.112***	(2.91)	0.125	(1.11)	0.102**	(2.26)
R*Big4	-0.065*	(-1.78)	-0.112	(-0.91)	-0.054	(-1.22)
D*Big4	-0.123*	(-1.94)	-0.133	(-0.71)	-0.127*	(-1.67)
R*D*Big4	-0.115	(-0.73)	-0.110	(-0.31)	-0.158	(-0.80)
Lit	0.182	(1.18)	-0.124	(-0.66)	0.238	(1.16)
R*Lit	0.049	(0.93)	-0.163	(-1.32)	0.036	(0.46)
D*Lit	0.033	(0.54)	-0.063	(-0.46)	0.041	(0.49)
R*D*Lit	-0.127	(-0.76)	-0.110	(-0.30)	-0.053	(-0.25)
Constant	-0.743***	(-5.92)	-0.242	(-0.70)	-0.836***	(-6.24)
Industry FE	Yes		Yes		Yes	
Year FE	Yes		Yes		Yes	
County FE	Yes		Yes		Yes	
			p-value			
R*D*CCSN(2)- R*D*CCSN(3)=0			0.504			
N	2806		688		1981	
adj. R2	0.3605		0.3033		0.3597	

This table presents the results of the following regression for affected areas and unaffected areas, respectively:

$$E_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 D_{it} + \beta_3 CCSN_{it} + \beta_4 R_{it} * D_{it} + \beta_5 R_{it} * CCSN_{it} + \beta_6 D_{it} * CCSN_{it} + \beta_7 R_{it} * D_{it} * CCSN_{it} + \beta_8 SIZE_{it} + \beta_9 R_{it} * SIZE_{it} + \beta_{10} D_{it} * SIZE_{it} + \beta_{11} R_{it} * D_{it} * SIZE_{it} + \beta_{12} MTB_{it} + \beta_{13} R_{it} * MTB_{it} + \beta_{14} D_{it} * MTB_{it} + \beta_{15} R_{it} * D_{it} * MTB_{it} + \beta_{16} LEV_{it} + \beta_{17} R_{it} * LEV_{it} + \beta_{18} D_{it} * LEV_{it} + \beta_{19} R_{it} * D_{it} * LEV_{it} + \beta_{20} Big4_{it} + \beta_{21} R_{it} * Big4_{it} + \beta_{22} D_{it} * Big4_{it} + \beta_{23} R_{it} * D_{it} * Big4_{it} + \beta_{24} Lit_{it} + \beta_{25} R_{it} * Lit_{it} + \beta_{26} D_{it} * Lit_{it} + \beta_{27} R_{it} * D_{it} * Lit_{it} + \gamma_j + \delta_t + \theta_k + \varepsilon_{it}$$

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.

Table 4: DID Analysis and Parallel Trends Assumption

	(1) E	t-stat.	(2) E	t-stat.
R	-0.095	(-0.62)	-0.009	(-0.04)
D	0.247*	(1.92)	0.303**	(2.04)
R*D	1.677***	(3.72)	1.595**	(2.64)
Post	-0.043	(-0.88)	-0.175	(-1.23)
R*Strike	-0.212*	(-1.88)	-0.127	(-1.55)
R*Strike*Post	0.208*	(1.83)	-0.040	(-0.55)
D*Strike	0.248**	(2.18)	0.063	(0.88)
D*Strike*Post	-0.009	(-0.22)	-0.127*	(-1.91)
R*D*Strike	0.540	(1.63)	-0.125	(-0.76)
R*D*Strike*Post	**0.506*** **	**(3.51)**	**0.388** **	**(2.50)**
SIZE	0.057***	(3.03)	0.064**	(2.09)
R*SIZE	0.046*	(1.83)	0.025	(0.61)
D*SIZE	-0.027	(-0.77)	-0.043	(-1.35)
R*D*SIZE	-0.288*	(-1.72)	-0.299	(-1.65)
MTB	-0.001	(-1.12)	-0.001	(-1.34)
R*MTB	0.000	(0.22)	0.001	(0.72)
D*MTB	0.002	(0.57)	0.001	(0.46)
R*D*MTB	-0.007	(-0.48)	-0.010	(-0.69)
LEV	-0.170	(-1.45)	-0.132	(-1.39)
R*LEV	-0.331**	(-2.56)	-0.295*	(-1.84)
D*LEV	-0.203	(-1.14)	-0.197	(-1.00)
R*D*LEV	0.288	(0.43)	0.402	(0.58)
Big4	-0.206*	(-1.71)	-0.206	(-1.44)
R*Big4	-0.018	(-0.24)	-0.032	(-0.31)
D*Big4	0.174	(0.56)	0.227	(0.81)
R*D*Big4	1.531	(1.27)	1.745	(1.48)
Lit	-0.179***	(-3.17)	-0.164*	(-1.95)
R*Lit	0.042	(0.55)	0.022	(0.29)
D*Lit	-0.241	(-1.19)	-0.274	(-1.33)
R*D*Lit	-1.015*	(-1.96)	-1.018*	(-1.99)
Constant	-0.116*	(-1.71)	-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		Yes	
Year FE	Yes		Yes	
County FE	Yes		Yes	
N	3376		3376	
adj. R2	0.1526		0.1526	

Column (1) presents the results of the following regression:

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

Column (2) presents the results of the following regression:

$$E_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 D_{it} + \beta_3 R_{it} * D_{it} + \beta_4 Post + \beta_5 R_{it} * Strike_{it} + \beta_6 R_{it} * Strike_{it} * Post + \beta_7 D_{it} * Strike_{it} + \beta_8 D_{it} * Strike_{it} * Post + \beta_9 R_{it} * D_{it} * Strike_{it} + \beta_{10} R_{it} * D_{it} * Strike_{it} * Post + \beta_{11} SIZE_{it} + \beta_{12} R_{it} * SIZE_{it} + \beta_{13} D_{it} * SIZE_{it} + \beta_{14} R_{it} * D_{it} * SIZE_{it} + \beta_{15} MTB_{it} + \beta_{16} R_{it} * MTB_{it} + \beta_{17} D_{it} * MTB_{it} + \beta_{18} R_{it} * D_{it} * MTB_{it} + \beta_{19} LEV_{it} + \beta_{20} R_{it} * LEV_{it} + \beta_{21} D_{it} * LEV_{it} + \beta_{22} R_{it} * D_{it} * LEV_{it} + \beta_{23} Big4_{it} + \beta_{24} R_{it} * Big4_{it} + \beta_{25} D_{it} * Big4_{it} + \beta_{26} R_{it} * D_{it} * Big4_{it} + \beta_{27} Lit_{it} + \beta_{28} R_{it} * Lit_{it} + \beta_{29} D_{it} * Lit_{it} + \beta_{30} R_{it} * D_{it} * Lit_{it} + Treatment - specific\ \ trend + Treatment - specific\ \ trend * R + Treatment - specific\ \ trend * D + Treatment - specific\ \ trend * R * D + \gamma_j + \delta_t + \theta_k + \varepsilon_{it}$$

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.

Table 5: Corroborating Evidence from Corporate Headquarters Relocations

Panel A: DID analysis	(1) E	t-stat.
R	-0.075	(-0.51)
D	0.212	(0.36)
R*D	0.171	(1.00)
R*Post	0.047	(0.85)
D*Post	0.576	(0.30)
R*D*Post	-0.039	(-0.66)
R* CCSN_Increasing_Relocation	-0.052	(-0.52)
R*CCSN_Increasing_Relocation*Post	0.000	(0.00)
D*CCSN_Increasing_Relocation	-0.173	(-1.33)
D*CCSN_Increasing_Relocation*Post	0.194	(1.41)
R*D*CCSN_Increasing_Relocation	-0.534	(-1.64)
R*D*CCSN_Increasing_Relocation*Post	**0.651***	**(1.72)**
SIZE	-6.143	(-0.44)
R*SIZE	0.005	(0.32)
D*SIZE	-2.415	(-0.29)
R*D*SIZE	-0.021	(-0.91)
MTB	-3.892	(-0.90)
R*MTB	0.007	(0.87)
D*MTB	6.954	(1.13)
R*D*MTB	-0.002	(-0.23)
LEV	0.187	(1.66)
R*LEV	-0.147	(-1.09)
D*LEV	-0.138	(-1.32)
R*D*LEV	0.213	(1.05)
Big4	-0.223	(-0.62)
R*Big4	0.021	(0.37)
D*Big4	-0.204	(-0.43)
R*D*Big4	-0.144	(-1.32)
Lit	0.000	(.)
R*Lit	-0.005	(-0.30)
D*Lit	-0.137	(-0.65)
R*D*Lit	-0.037	(-0.74)
Constant	0.237	(0.28)
Industry FE	Yes	
Year FE	Yes	
County FE	Yes	
N	156	
adj. R2	0.3124	

This table presents the results of the following regression:

$$E_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 D_{it} + \beta_3 R_{it} * D_{it} + \beta_4 Post + \beta_5 R_{it} * CCSN\_Increasing\_Relocation_{it} + \beta_6 R_{it} * CCSN\_Increasing\_Relocation_{it} * Post + \beta_7 D_{it} * CCSN\_Increasing\_Relocation_{it} + \beta_8 D_{it} * CCSN\_Increasing\_Relocation_{it} * Post + \beta_9 R_{it} * D_{it} * CCSN\_Increasing\_Relocation_{it} + \beta_{10} R_{it} * D_{it} * CCSN\_Increasing\_Relocation_{it} * Post + \beta_{11} SIZE_{it} + \beta_{12} R_{it} * SIZE_{it} + \beta_{13} D_{it} * SIZE_{it} + \beta_{14} R_{it} * D_{it} * SIZE_{it} + \beta_{15} MTB_{it} + \beta_{16} R_{it} * MTB_{it} + \beta_{17} D_{it} * MTB_{it} + \beta_{18} R_{it} * D_{it} * MTB_{it} + \beta_{19} LEV_{it} + \beta_{20} R_{it} * LEV_{it} + \beta_{21} D_{it} * LEV_{it} + \beta_{22} R_{it} * D_{it} * LEV_{it} + \beta_{23} Big4_{it} + \beta_{24} R_{it} * Big4_{it} + \beta_{25} D_{it} * Big4_{it} + \beta_{26} R_{it} * D_{it} * Big4_{it} + \beta_{27} Lit_{it} + \beta_{28} R_{it} * Lit_{it} + \beta_{29} D_{it} * Lit_{it} + \beta_{30} R_{it} * D_{it} * Lit_{it} + \gamma_j + \delta_t + \theta_k + \varepsilon_{it}$$

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.

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	

This table presents the regression results for firms in climate-vulnerable industries and climate non-vulnerable industries, classified based on either the Fama French 48 industry framework (Columns 1 and 2) or the GICS framework (Columns 3 and 4), respectively:

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

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.

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)
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	

This table presents the regression results for firms during times with higher (Column 1) or lower (Column 2) media coverage of climate risk, respectively:

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

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.

Table 8: Channel Analysis-the Role of Cash Holdings

	(1) Cash	t-stat.
CCSN	**0.026*** **	**(4.88)**
SIZE	-0.011**	(-3.23)
MTB	0.001**	(4.04)
LEV	-0.123***	(-5.50)
CFO	-0.012***	(-25.77)
CFO_sd	0.005**	(3.33)
NWC	0.015***	(7.68)
Dvc	-0.053	(-1.52)
R&D	0.076***	(6.47)
Capx	-0.473*	(-2.16)
Constant	0.350***	(35.83)
Industry FE	Yes	
Year FE	Yes	
N	15477	
adj. R2	0.5276	

This table presents the results of the following regression:

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

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.

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)
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	

This table presents the results of the following regression:

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

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

This table presents the path analysis results which distinguish the direct impact of CCSN on REM from the indirect impact via conditional conservatism. The path coefficients are obtained by estimating the following structural equation model:

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

$$C\_score_{it} = \beta_0 + \beta_1 CCSN_{it} + Fixed\ \ effects + \varepsilon_{it}$$

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.