Measuring Corporate Weather Exposure using Computational Linguistics*

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June 2019

Abstract

We create one of the first large-scale firm-level measures of corporate weather exposure based on the frequency of the word *weather* in about 100,000 annual reports from 1994 to 2018. We find that corporate weather exposure is currently near its high point and has increased dramatically over time. For 2018, our geospatial analysis shows that firms headquartered in the central and southeastern U.S. are currently the most weather exposed, and the top quartile of firms most exposed are worth about \$9.7 trillion in sum. We further show that our measure increases in a difference-in-differences manner for firms impacted by hurricanes, correlates well with weather-dependent firms, and decreases during Republican presidencies when climate regulation is often reduced. Our exposure measure is also statistically and economically associated with such firm-level outcomes as increased capital expenditures, decreased profitability, and increased volatility of profits and returns.

JEL Classification: D72, O13, Q54

*We thank seminar participants at the 2019 Washington Accounting Research Symposium, Georgetown University, and the University of Michigan.

1 Introduction

Identifying which firms are exposed to weather-related impacts ("weather exposure") is crucial in an age when climate change and its impact on the weather may soon cost the global economy 20 percent of its GDP every year (Stern, 2007). However, surveys of climate economics argue that a lack of systematic micro data for this construct poses "long-standing challenges for understanding the historical, contemporary, and future economic consequences of climate" (Dell et al., 2014, p. 741).[1] For example, recent finance studies on weather derivatives examine the overall market characteristics of these instruments but are largely unable to identify individual market participants and their weather exposure (e.g., Purnanandam and Weagley, 2016; Weagley, 2019). In particular, Engle et al. (2019, p. 35) create a market-wide climate factor and call for "more and better data to measure firm-level climate risk exposures." One source of firm-level data is the CDP (formerly the Carbon Disclosure Project) surveys, but these are voluntary and cover only a limited set of firms over a few years (e.g., Goldstein et al., 2019). We therefore create a systematic measure of weather exposure for every public U.S. firm using all annual reports from 1994 to 2018.

Annual reports are ideal for measuring corporate weather exposure because these reports provide an ongoing overview of a company's operations and are closely monitored by regulators and auditors. For each annual report, we measure the frequency of the term *weather*. We use the word *weather* instead of related phrases like *greenhouse gas* or *climate change*, which are narrower in scope and whose political connotations in the U.S. may deter some companies from using them.[2] This approach confers several advantages in addition to being broad in scope and simple. First, we impose no survival criteria beyond being a publicly

[1]Nordhaus (2006, p. 3511) similarly emphasizes the importance of micro data, arguing that "virtually all studies focus on national data," and future research should try "disaggregating below the national level." In addition, in 2019, Rostin Behnam, a Commissioner of the Commodity Futures Trading Commission, initiated a report on the economic risks of climate, noting that "it's abundantly clear that climate change poses financial risk to the stability of the financial system" (Davenport, 2019). Also, Angel Gurria, the leader of the Organisation for Economic Cooperation and Development, argued in 2015 that more research is needed "to understand and measure [climate] risks" (see `https://oe.cd/2C2`).

[2]We nonetheless perform robustness checks where we show that using these related terms do not alter our inferences.

traded firm, making this one of the largest studies on corporate weather exposure. Second, our approach facilitates new quasi-experiments, various cross-sectional and time-series analyses, and the estimation of firm-level dollar-value impacts. Third, we are not aware of any other regulatory filings that are as systematically informative about weather exposure.[3] Finally, an important assumption we make is that on average, firms with material exposure to the weather will mention that in their annual reports. This is a reasonable assumption since omitting material information from an annual report can exacerbate investor information asymmetry and stock liquidity problems, and can also expose a firm to shareholder lawsuits, credibility concerns, and regulatory penalties (e.g., Leuz and Wysocki, 2016; Skinner, 1997).[4]

One initial result is that firms have reported on weather exposure for a long time, although mentions of *weather* in annual reports increase dramatically over the sample period. For example, in 2018, about 65 percent of firms mention *weather* once or more their annual report, compared to only 25 percent of firms in 1994. Mentions of other weather-related terms also increase significantly. From 1994 to 2002, the average firm makes no mention of *climate change* in their annual report, whereas since 2012, the average firm mentions *climate change* about 1.5 times per year in their annual report. Similar patterns obtain for the terms *greenhouse gas*, *carbon dioxide*, and *global warming*. *Global warming*, for example, increases in prevalence 15-fold from 1994 to 2018. In addition, considerable value is exposed to weather. For 2018, the top quartile of firms most exposed are worth \$9.7 trillion in sum.

Weather typically refers to current or short-run atmospheric conditions. Our validity tests for measuring weather exposure focus on how well our measure corresponds to the conditions in which weather would likely play role in a firm's operations. We find that weather exposure is significantly higher for firms whose business models likely depend on the environment: utility, energy, and food production firms. By contrast, weather exposure is

[3]The SEC, the SASB, and several large institutional investors are currently debating requiring standardized climate disclosures from firms, but have not yet reached a definitive conclusion (e.g., Plumer, 2019; Rubin, 2019).

[4]Li et al. (2013, p. 406) similarly depend on managers reporting truthfully in their annual reports regarding their competitive situation. As with that study, we assume that managers are informed parties who are aware of their firms' weather exposure.

significantly lower for firms whose business models likely depend less on the environment: financial services and healthcare firms. However, industry factors alone explain only a fraction of our measure's variation. We also find that larger firms are proportionally more exposed to weather, and weather exposure decreases during Republican presidencies, which is consistent with the idea that the Republican party (relative to the Democratic party) reduces corporate weather exposure by reducing expensive climate-related enforcement actions and regulations (e.g., Republican National Committee, 2019; Turner and Isenberg, 2018). Our geospatial analysis shows that location also matters: Firms headquartered in the central and southeastern U.S. are currently the most weather exposed.

Turning to our time-series analysis, Dell et al. (2014, Section 2.1) argue that the long-run phenomenon of climate change may be a candidate for why our weather exposure measure would increase significantly over our sample period. A widely accepted proxy for climate change is the level of atmospheric carbon dioxide (CO_2) in the environment, as measured by the Mauna Loa Observatory in Hawaii (e.g., Keeling et al., 1976).[5] We find statistically significant positive relations between our weather exposure measure and atmospheric CO_2 after controlling for firm-fixed effects and sample-wide trends in annual report length.

To further validate that our measure proxies for corporate weather exposure, we use two quasi-experimental settings. An advantage of using quasi-experiments is that we can isolate plausible treatment and control samples that enable us to explicitly test whether our measure corresponds to changes in corporate weather exposure. The difference-in-differences nature of these tests also controls for any common latent trends in macroeconomic conditions and annual report dialect. The importance of incorporating this technique into our analysis is evident in Dell et al. (2014, p. 743), who argue that given the complexities of structural climate-economic models, researchers should combine quasi-experiments and cross-sectional analysis whenever possible. Carleton and Hsiang (2016) similarly argue that any analysis of climate economics should incorporate a "dose-response" framework.

[5]For more detail, see `https://www.esrl.noaa.gov/gmd/ccgg/trends/`.

Our quasi-experiments involve two major hurricanes, Hurricane Katrina and Hurricane Sandy. In 2005, Katrina hit several southeastern states in the U.S., and in 2012, Sandy hit several northeastern coastal states. Since these extreme weather events affected regions that have not seen such powerful storms in recent history, we argue that managers' perception of corporate weather exposure plausibly changed for the storm-affected firms relative to other firms (e.g., Brinkley, 2007; Sobel, 2014).[6] These hurricanes are ideal for our empirical goals because they provide a strong difference-in-differences setting: Firms headquartered in the storm-affected states can serve as the treatment sample, and firms headquartered in the non-affected states can serve as the control sample. Using a pre-post storm research design with firm-fixed effects, we find that for both storms, our weather exposure measure increases significantly in a difference-in-differences manner for firms headquartered in the storm-affected states. Moreover, the economic magnitudes of the results are larger for Katrina, which caused about twice as much damage as Sandy (Kaleem and Wallace, 2012). Taken together, these findings provide additional evidence that our measure is capturing weather exposure.

Lastly, it is common practice to validate new measures by associating them to relevant financial metrics and corporate operating decisions (e.g., Baker et al., 2016, Section IV.A). These associations also enable us to "dollarize" our weather exposure measure. To alleviate concerns that across-firm or across-year variations are driving our results, we use firm- and year-fixed effects as controls. In the short run, firms likely cannot significantly control their weather exposure and therefore must adapt (proactively or reactively) accordingly. For example, prior studies such as Barreca et al. (2015, 2016) and Dell et al. (2012) argue that weather exposure necessitates capital expenditures (CAPEX) on climate mitigators such as cooling equipment. Consistent with this idea, we find that our *weather* measure is significantly positively associated with a firm's current and future CAPEX spending after

[6] If this does not occur, we assume we would find no difference-in-differences results, although we cannot directly test this exclusion restriction. This limitation applies to all difference-in-differences research designs. See Section 4.2.2 for more detail on this point and the setting.

controlling for other known drivers of CAPEX. In terms of dollar-value impact for the average firm in the sample, a one standard deviation increase in the *weather* measure is associated with about a $300,000 increase in annual CAPEX spending for a given year and additional increases in CAPEX in subsequent years.

We also find that weather exposed firms are significantly less profitable in terms of return on assets (ROA) and more volatile in terms of future ROA and returns. These findings speak to the concerns raised by regulators such as the Commodity Futures Trading Commission that weather may serve as a significant source of volatility for the financial markets going forward (Davenport, 2019). In terms of dollar-value impact for the average firm in the sample, a one standard deviation increase in the *weather* measure is associated with about a $600,000 decrease in net income for a given year and additional decreases in net income in subsequent years. This result comports well with our finding that weather exposed firms have relatively high CAPEX spending. These results are also robust to other measures of weather exposure. Although our results are not necessarily casual, a plausible interpretation of this micro evidence is that material weather exposure necessitates proactive and reactive adaptation costs for firms that increase CAPEX, reduce profitability, and increase total firm volatility.

Overall, we provide one of the first systematic firm-level measures of corporate weather exposure, which is a construct that researchers have argued is lacking in data but central to climate research and the design of climate policy (e.g., Hsiang et al., 2017). A key advantage of our measurement technique is that it we can apply it to all public firms over many years. Our resulting measure can then be linked to relevant financial outcomes to estimate its dollar-value associations at the firm level. By comparison, the most recent CDP Climate Change Report only provides aggregate dollar-value impacts of climate using one year of data and less than 2,000 voluntarily participating firms.[7] Bloomberg climate data are similarly

[7] The CDP has released these reports for various countries since 2013, and prior reports include fewer firms. For the 2018 global report, see `https://www.cdp.net/en/research/global-reports/global-climate-change-report-2018/climate-report-risks-and-opportunities`. Goldstein et al. (2019) use these data to provide a perspective on the climate exposure of 1,600 firms for the year 2016.

limited in terms of covered firms and years (e.g., Grewal et al., 2017). Christensen, Hail, and Leuz (2019, p. 119) argue that although analyses that use these data can be useful, they are not substitutes for a systematic and comprehensive approach to studying climate reporting.

The remainder of this study is organized as follows. In Sections 2 and 3, we discuss our conceptual underpinnings and the data. In Section 4, we provide our empirical results. In Section 5, we conclude.

2 Conceptualizing corporate weather exposure

Climate primarily refers to long-run atmospheric conditions, while weather typically refers to the short-run (Dell et al., 2014, p. 741). A firm's business model can be exposed to weather in several ways (e.g., Goldstein et al., 2019). First, weather may impact its operations directly by necessitating risk planning, human capital development, and investment in hard capital assets. This impact may not be linear: moderate weather may have no impact, but hotter and severe weather could have a disproportionate impact. Furthermore, this impact may not be direct but due to its effects on suppliers, employees, and customers, and to mediating factors such as weather-related legislation that disrupts some portion of a firm's production process and logistics. As a result, it is implausible to expect to have a definitive numerical measure of corporate weather exposure.

To the extent weather has a material impact on a firm's business model and managers are aware of it, they have several incentives to report truthfully in annual reports. Withholding material information can potentially lead to future lawsuits and damage management reputation. It may also invite privately informed speculators to trade in a firm's shares, worsening its liquidity. Consequently, prior accounting studies that linguistically analyze annual reports such as Li et al. (2013, p. 406) assume that managers report truthfully on average. As a result, the annual reports in our setting are likely a systematic source of weather exposure information. Again, however, this information is unlikely to be numerically one-dimensional. It could appear in different parts of the annual report depending on whether it is a one-time or ongoing exposure, and a firm could use a variety of words and contexts to describe its situation.

Prior studies such as Li et al. (2013) that use annual reports for their linguistic content have eschewed more complex computational techniques in favor of a simple count of words. We therefore count the word *weather* in each annual report and then control for firm size, report length, and other factors. We choose the word *weather* over other weather-related terms such as *climate change*, *greenhouse gas*, and *global warming* because some of the latter terms are politically charged in the current U.S. political climate, and also because the term *weather* likely has a wider scope than these other terms. In robustness tests, however, we combine all the above terms to create another proxy for a firm's weather exposure. We view this approach as an alternative to more complex linguistic approaches such as checking close occurrences of the terms *weather* and *risk* or some other contextual word patterns. We have no reason to believe that these contextual approaches are better suited for our goal than simple word counts.

Our statistical analyses take a simple form. After constructing the weather exposure measure, we document its cross-sectional and time-series properties. We then show its behavior around a natural quasi-experiment, further validating our measure. We then "dollarize" the measure by correlating it with relevant financial and operational outcomes. Finally, we conduct robustness tests using an alternative measure that combines several weather-related terms. Note that we do not attempt to explicitly model any endogenous elements of the measures. Instead, we use firm- and year-fixed effects whenever possible to control for across-firm variation as well as any sample-wide time-series effects. Our approach increases our confidence in attributing our results to the within-firm, within-year variation in the measure, and not to firm or year effects.

3 Overview of the data sources

We use the Security and Exchange Commission's (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system to download all the annual reports (form 10-K) filed by U.S. public firms from 1994 to 2018. The SEC began phasing in firms to its electronic filing system in 1994, and electronic filing became mandatory in 1996. We remove observations with missing financial data and impose no other survival criteria. The final sample covers 97,402 annual reports for 10,588 unique firms.

For each annual report, we use Perl to count every occurrence of *weather*, *climate change*, *greenhouse gas*, *carbon dioxide*, and *global warming*.[8] As Sections 1 and 2 explain, most of our analyses use the *weather* measure given its relative objectivity, wide scope, and empirical tractability. We use firm-fixed effects to control for any cross-sectional variation in firms' annual report practices, and year-fixed effects to control for any sample-wide time clustering in annual report practices (e.g., due to any sample-wide increase in weather exposure). We also control for several widely used readability indices and, to achieve scaling, the number of words in each annual report. All of the results are qualitatively similar when we replace the number of words in each report with alternative measures of report length, including file size, page counts, and character counts (e.g., Loughran and McDonald, 2014). We also use the log transformation of the *weather* measure, although our inferences are similar when we do not log transform this measure (Hsiang, 2016, p. 58).

We obtain firm financial data from Compustat, CRSP, I/B/E/S, and Thomson Reuters. We also use Hurricane Katrina and Hurricane Sandy as quasi-experiments. Since Hurricane Katrina hit late in 2005, we create a post indicator variable that equals zero for annual reports filed in 2004 and 2005, and one for annual reports filed in 2006 and 2007.[9] Similarly,

[8] Li et al. (2013), Mäntylä et al. (2018), and Turney (2002) argue that simple computational linguistics techniques such as word frequencies often perform equally well compared to more complicated techniques. We use *climate change* rather than *climate* because *climate* can be ambiguous.

[9] This approach is appropriate because the vast majority of annual reports filed in 2005 are filed in February, 2005 and pertain to fiscal year 2004, and the vast majority of annual reports filed in 2006 are filed in February, 2006 and pertain to fiscal year 2005.

since Hurricane Sandy hit late in 2012, we create a post indicator variable that equals zero for annual reports filed in 2011 and 2012, and one for annual reports filed in 2013 and 2014. The two-year post window gives firms time to adjust their annual reports. We also use firm-fixed effects in these tests.

We measure stock liquidity using percent bid-ask spreads and Amihud illiquidity and compute these measures as denoted in Appendix A. Prior studies often use firm- and year-fixed effects to isolate the information component of spreads, which is the approach we follow (e.g., Bushee et al., 2010; Guay et al., 2016; Lang et al., 2012; Schoenfeld, 2017).[10] Since all of our regressions are run at the firm-level, we two-way cluster standard errors by firm and year whenever possible, which lets the error terms be correlated within a firm and across all firms for a given time period. The tables denote the clustering method. All the variables, along with their sources and exact equations, are tabulated in Appendix A. Table 1 provides winsorizing details and notes that our inferences are not sensitive to winsorizing.

4 Empirical results

4.1 Univariate statistics

Table 1, Panel A shows that the average annual report in our sample contains 2.53 mentions of the term *weather*. Moreover, in 2018, about 65 percent of annual reports mention *weather* at least once, whereas in 1996, only 25 percent of annual reports mention *weather* at least once. The average and median firm in our sample has about \$7 billion and \$530 million in assets, respectively. For 2018, firms in the top quartile of the *weather* measure are worth about \$9.7 trillion in sum. As for the readability indices, lower Flesch-Kincaid scores signify annual reports that are more difficult to read, whereas higher scores of the Gunning Fog and Smog indices signify increased reading difficulty. The Flesch-Kincaid readability

[10]To address any skewness in Amihud illiquidity, we follow Lang and Maffett (2011, p. 114) and ensure that our inferences are qualitatively similar when we use Amihud decile rankings and a modified Amihud that deflates dollar trading volume by market value of equity.

average of 15.75 suggests that the reading difficulty of the average annual report is at the college-graduate level. Table 1, Panel B provides the Pearson correlations for the corporate weather exposure measures. The significant positive correlations among all the measures suggest that they are capturing a common underlying construct.

Figure 1 uses our most recent data from 2018 to provide a spatial look at weather exposure for firms headquartered in a given state. We create an equal-weighted state-level weather exposure measure by averaging the *weather* measure for all the firms headquartered in a given state. We then rank order the state-level measure to see which states are the most weather exposed. The most weather-exposed states include Louisiana, South Dakota, Idaho, Kansas, Missouri, and Oklahoma. The least weather-exposed states include West Virginia, Maryland, California, Maine, and Massachusetts. Weather exposure is thus pervasive across the country, although it is concentrated in the central and southern states. We next ensure that our spatial analysis is capturing business activity located in a given state. García and Norli (2012, Table 2) find that although virtually all firms have considerable operations located in their headquarter states, smaller firms (firms with market values below $2 billion) have significantly more of their operations located in their headquarter states relative to larger firms. We therefore check for and find similar spatial results when we replicate our chart using only firms with market values below $2 billion.

Turning to the time-series properties of our measure, Figure 2 shows that *weather* mentions in annual reports increase about 500 percent for the average firm over the sample period, with an especially strong upward trend from 2009 to 2014. The other weather terms also increase significantly over the sample period. Figure 3 shows that from 1994 to 2002, the average firm makes virtually no mention of *climate change* in their annual report. However, by 2011, the average firm mentions *climate change* in their annual report at least once. Figure 4 shows that the term *greenhouse gas* is mentioned on average more than once in 2018 annual reports. Figure 5 shows that in 2013, mentions of *carbon dioxide* increased 800 percent from a decade earlier. Figure 6 shows about a 1,500 percent increase in *global* *warming* mentions from 1994 to 2013. All of these measures also correlate significantly with atmospheric CO_2, as shown in Figure 7. To put these results into context, the average length (in words) of an annual report increases by about 200 percent from 1994 to 2018. Our corporate weather exposure measures increase far more rapidly than this.[11]

4.2 Sources of cross-sectional variation

4.2.1 Firm and time-series attributes

Our first test examines the industry characteristics of our measure. We argue that firms with relatively high weather exposure include utility, energy, food production, tobacco, and textile firms. By contrast, we argue that firms with relatively low weather exposure include financial services and healthcare firms. To test this idea, we regress the *weather* measure on indicator variables representing the aforementioned industries and year-fixed effects. Table 2, Column 1 shows that the *weather* measure is significantly higher in the predicted high-exposure industries relative to all the other industries, and significantly lower in the predicted low-exposure industries relative to all the other industries. The economic magnitudes are also significant. The *weather* measure is about 193.0 percent higher for utility firms, 92.0 percent higher for energy firms, and 37.7 percent higher for food and textile firms relative to other firms (1% level). By contrast, the *weather* measure is about 43.7 percent lower for healthcare firms and 34.6 percent lower for financial firms relative to other firms (1% level).

The next test focuses on the temporal aspects of our weather exposure measure that were previously absorbed by the year-fixed effects. As Figure 2 shows, over the sample period our weather exposure measure increases about 500 percent, which far exceeds the contemporaneous 200 percent increase in annual report length. Dell et al. (2014, Section 2.1) argue that the long-run phenomenon of climate change is a clear candidate for a driver of this. A

[11] We also find that the frequency of *weather* in books is relatively stable over the majority of our sample period, which suggests that our measure is not capturing any significant evolution of the weather-related English vernacular (see `https://books.google.com/ngrams/graph?content=weather&case_insensitive=on&year_start=1994&year_end=2008&corpus=15&smoothing=10`).

widely accepted proxy for climate change is the level of atmospheric CO_2 in the environment, as measured by the Mauna Loa Observatory in Hawaii (e.g., Keeling et al., 1976). In Table 2, Column 2, we therefore regress the weather exposure measure on its contemporaneous atmospheric CO_2 value. We also include firm-fixed effects but not year-fixed effects, as Dell et al. (2014, Section 2.1) argue that given the tight link between atmospheric CO_2 and the passage of time, including year-fixed effects in such a test is over-controlling and leaves no residual variation. Table 2, Column 2 shows that the *weather* measure is significantly positively associated with its contemporaneous value of atmospheric CO_2. A one standard deviation increase in CO_2 is associated with a 16.8 percent increase in the *weather* measure (1% level). We also find qualitatively similar results when we use the U.S. and global mean surface temperatures in place of atmospheric CO_2.

Our next tests focus on the political environment. Relative to Democratic presidencies, Republican presidencies are known for reducing environmental regulations and enforcement actions (e.g., Republican National Committee, 2019; Turner and Isenberg, 2018). For example, a Republican government may roll back expensive climate-related compliance changes to a firm's production process. We therefore create an indicator variable that equals 1 during Republican presidencies and 0 during Democratic presidencies.[12] We also replace the year-fixed effects with a year time-trend variable because the year-fixed effects are subsumed by the indicator for Republican presidencies. After controlling for the time trend and firm-fixed effects, Table 2, Column 3 shows that the *weather* measure decreases by about 4.3 percent during Republican presidencies relative to Democratic presidencies (1% level).

A potential issue with the above test of Republican presidencies is that except for the Trump presidency, Republican presidencies occur mainly in the earlier years of the sample, which may confound the analysis with any non-linear time trend in the data.[13] We therefore

[12]Republican presidencies include the years 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2017, and 2018. Since presidential elections occur in November, and the majority of firms file their annual reports in February, firms have time to alter their annual reports after a presidential election if necessary. To the extent that firms do not adjust their annual reports in time, this biases against our finding a result.

[13]Any confounding time effect must be non-linear because we include a linear time trend.

run the test using only the Trump presidency that occurs after the Obama presidency while still including a year time trend. Using the final year of the Obama presidency as the baseline control year, we create an indicator that equals one during the Trump presidency (2017 and 2018) and 0 during 2016. Table 2, Column 4 shows that the *weather* measure decreases by about 2.4 percent (1% level) during the first two years of the Trump presidency relative to the final year of the second Obama presidency (the difference in magnitudes could be due to low power). This result obtains despite the fact that there were more external weather events in 2017 and 2018 combined relative to 2016.[14] These findings corroborate the results in Table 2, Column 3.

All of the regressions in Table 2 also control for firm size, annual report length, and the report readability indices. Controlling for annual report length is important because it eliminates any firm-specific or macro trends in report length that may be correlated with the frequency of *weather* mentions. Another result of note is that regardless of the fixed-effect structure, weather exposure is increasing in total assets in all the regressions. One speculation is that as firms acquire new assets or expand into new business lines, they become exposed to more weather systems. In addition, the relatively high R^2 values in Table 2, Columns 5 and 6 also suggest that the firm- and year-fixed effects are capturing some, but not all, of the variation in the frequency of *weather* mentions. However, Table 2, Column 1 shows that controlling for industry alone leaves significant residual variation in the frequency of *weather* mentions. This suggests that weather exposure is not just an industry phenomenon.

4.2.2 Hurricanes as quasi-experiments

To further assess the validity of our corporate weather exposure measure, we use Hurricane Katrina and Hurricane Sandy as difference-in-differences quasi-experiments. These extreme weather events affected regions that have not experienced such powerful storms in recent history. Therefore, management may have been unable to precisely predict these

[14]See `https://www.weather.gov/mob/events`.

weather events and their impact on the firm's business model until these events happened (e.g., Brinkley, 2007; Sobel, 2014). That is, we argue that managers' perception of (material) corporate weather exposure plausibly changed for the storm-affected firms relative to other firms. Since we cannot directly test this exclusion restriction, we assume we would find no difference-in-differences results if it does not hold. This is a limitation of all difference-in-differences research designs.

Recall that for Hurricane Katrina, we create an indicator variable that equals zero for annual reports filed in 2004 and 2005, and one for annual reports filed in 2006 and 2007. We follow Brinkley (2007) and denote the storm-affected firms as those headquartered in Alabama, Florida, Louisiana, or Mississippi. For Hurricane Sandy, we create an indicator variable that equals zero for annual reports filed in 2011 and 2012, and one for annual reports filed in 2013 and 2014. We follow Sobel (2014) and denote the storm-affected firms as those headquartered in Connecticut, Delaware, Massachusetts, Maine, New Hampshire, New Jersey, New York, Rhode Island, or Vermont. Firms headquartered in the non-affected states serve as the control sample for each storm. The two-year post window gives firms time to adjust their annual reports, and we use firm-fixed effects with clustered standard errors.[15]

In Table 3, we regress the *weather* measure on the interaction of the post Katrina indicator and the storm-affected states using the sample period of 2004 to 2007, which provides four years of data: two years before the storm (the pre period) and two years after the storm (the post period). Note that we do not include the state indicators as main effects since they are firm-invariant and subsumed by the firm-fixed effects. Table 3, Column 1 shows that firms based in the storm-affected states exhibit a statistically significant 19.9 percent difference-in-differences increase in the *weather* measure after summing the appropriate coefficients (1% level). We then replicate the difference-in-differences analysis for Hurricane Sandy by regressing the *weather* measure on the interaction of the post Sandy indicator and the storm-

[15]To the extent that firms do not adjust their annual reports in time, this biases against our finding a difference-in-differences result. See fn. 9 for more detail on how our setup appropriately links the timing of the hurricanes to the filing of the annual reports.

affected states using the sample period of 2011 to 2014, which again provides four years of data: two years pre and two years post. Table 3, Column 2 shows that firms based in the storm-affected states exhibit a statistically significant 7.7 percent difference-in-differences increase in the *weather* measure after summing the appropriate coefficients (1% level). The lower magnitude of the Sandy result relative to the Katrina result is to be expected given that Katrina was a more powerful storm that caused about twice as much damage as Sandy (Kaleem and Wallace, 2012).

For both Katrina and Sandy, we control for firm-fixed effects, firm size, and annual report length. The relatively high R^2 values signify that the firm-fixed effects are appropriately eliminating the time-invariant elements of the annual reports. The tight pre-post research design further mitigates any possibility of hurricane-unrelated confounding events, and the lower economic magnitudes of the results for Sandy are consistent with the relative sizes of the storms. In sum, our difference-in-differences findings provide additional evidence that we are capturing weather exposure with our measure.

4.3 Corporate weather exposure and financial outcomes

An important assumption thus far is that our textual measure captures a firm's true weather exposure. That is, we assume that management is informed about their firm's weather exposure and is strongly incentivized to truthfully make these disclosures.[16] Following Baker et al. (2016, Section IV.A), we next show that our measure is associated with relevant financial outcomes, starting with CAPEX.[17] Prior studies argue that weather exposure necessitates capital expenditures on climate mitigators such as cooling and other equipment (e.g., Barreca et al., 2015, 2016; Dell et al., 2012). We therefore test whether our

[16]Li et al. (2013, p. 406) similarly assume that for annual report disclosures about competition, "managers have a reasonably accurate perception of the 'true' amount of competition they face, whatever its form, and that their disclosures about competition in the 10-K filing are a reasonably accurate reflection of these perceptions."

[17]We recognize that we have switched the weather exposure measure from a dependent variable to an independent variable. Our previous hurricane quasi-experiments and our use of fixed effects in the current regressions represent our attempt to control for any endogeneity in this measure.

corporate weather exposure measure is associated with current and future capital expenditures at the firm level by regressing CAPEX scaled by assets on the *weather* measure, firm- and year-fixed effects, and several other known drivers of CAPEX.[18] All of the variables must be interpreted not in levels but as deviations from their firm- and year-fixed-effect averages. That is, any cross-sectional variation in firms' disclosure practices or their CAPEX levels are controlled for by the firm-fixed effects, and likewise for year-fixed effects and any sample-wide time clustering in CAPEX and disclosure practices.

Table 4, Columns 1 to 3 show that the *weather* measure at $t = 0$ is associated with increased CAPEX at $t = 0$ (1% level), $t + 1$ (1% level), and $t + 2$ (10% level). A one standard deviation increase in the *weather* measure is associated with about a 0.17 percentage point increase in scaled CAPEX in $t = 0$ and $t + 1$, which approximately translates to an economically meaningful 10 percent increase from the sample median CAPEX, or a dollar-value impact of about $300,000 annually for the average firm in the sample.[19] In $t + 2$, the CAPEX effect is still significant but declines in magnitude. Net cash flows, Q, leverage, returns, return volatility, analyst following, and institutional ownership are also associated with CAPEX in the expected directions (e.g., Almeida et al., 2004; Kaplan and Zingales, 1997; Titman et al., 2004).

To test whether our corporate weather exposure measure is associated with ROA at the firm level, we regress current and future ROA on the *weather* measure, firm- and year-fixed effects, and several other known drivers of ROA such as leverage. Table 4, Columns 4 to 6 show that the *weather* measure at $t = 0$ is associated with decreased ROA at $t = 0$ (5% level), $t+1$ (1% level), and $t+2$ (5% level). The effect is similar in magnitude in $t = 0$ and $t+2$ but is strongest in $t + 1$. A one standard deviation increase in the *weather* measure is associated with about a 0.45 percentage point decrease in scaled ROA in $t + 1$, which approximately translates to an economically meaningful 15 percent decrease from the sample median ROA,

[18]Our inferences are qualitatively similar when we scale CAPEX by Tobin's Q (e.g., Badertscher et al., 2013).

[19]Note that the standard deviation of the natural log of one plus the *weather* measure is 0.93, whereas the standard deviation of the raw *weather* measure is 6.13 (see Table 1, Panel A).

or a dollar-value impact of about $600,000 annually for the average firm in the sample.

In Table 4, Column 7, we also find that a one standard deviation increase in the *weather* measure is associated with about a 0.27 percentage point increase in future ROA volatility as measured over the three year period of a given fiscal year and the two years that follow it ($t = 0, 1, 2$).[20] This represents an 11 percent increase from the sample median ROA volatility. Table 4, Column 8 further shows that a one standard deviation increase in the *weather* measure is associated with about a 0.05 percentage point increase in future return volatility as measured over the subsequent fiscal year ($t + 1$). This represents a 3 percent increase from the sample median return volatility. We again control for firm- and year-fixed effects and other relevant variables in the volatility tests. Taken together, these findings suggest that weather exposure significantly increases firm volatility.

In sum, the evidence in Table 4 suggests that firms respond to their weather exposure by significantly increasing current and future capital expenditures. This finding comports well with the result that exposed firms have lower and more volatile current and future profitability. The market also appears to recognize these effects as evidenced by the significant positive association between weather exposure and return volatility. However, we cannot establish causality because there are several reporting and economic channels through which CAPEX can positively or negatively impact profitability, and profitability can impact return volatility.

One benefit to managers of weather reporting is that a firm's stock becomes more liquid. Table 5 therefore regresses percent bid-ask spreads and Amihud illiquidity on the *weather* measure at the firm level. We assume that investors react relatively quickly to information in the annual report and compute average liquidity over a short, 4-day window that starts at and includes the annual report filing date. All regressions are within-firm and within-year, thereby allowing each firm to serve as its own control and eliminating any time trends in the data. All of the variables must therefore be interpreted not in levels but as deviations

[20]Our inferences are similar when we only include ROA in $t = 1, 2$.

from their firm- and year-fixed-effect averages. That is, any cross-sectional variation in firms' disclosure practices or their liquidity levels are controlled for by the firm-fixed effects, and likewise for year-fixed effects and any sample-wide time clustering in liquidity (e.g., due to technological advances) and disclosure practices (e.g., due to a sample-wide increase in weather exposure).

Table 5, Columns 1 and 2 show that the *weather* measure is associated with decreased percent spreads and decreased Amihud illiquidity (5% and 1% levels). A one standard deviation increase in the *weather* measure is associated with a 0.06 decrease in percent spreads and a 0.17 decrease in Amihud illiquidity. Several of the control variables are also associated with liquidity in the expected directions (e.g., Chordia et al., 2000; Holden et al., 2013). Taken together, these findings suggest that information about corporate weather exposure increases stock liquidity. To put these results into context, Bushee et al. (2010, p. 14) find that percent spreads decrease by about 0.11 for a one standard deviation increase in their press coverage measure. Also, Balakrishnan et al. (2014, p. 2249) report that losing an analyst causes Amihud to increase by 0.024 on average.

In Table 5, Columns 3 and 4, we use spreads and Amihud illiquidity measured over a longer, 31-day window that starts at and includes the annual report filing date. The findings are again statistically significant, which confirms that the increased liquidity observed in the 4-day window persists. Furthermore, the long-window result increases in economic magnitude relative to the short-window result, which suggests that it takes time for some investors to fully process information about corporate weather exposure. Many of the control variables are also significant in the same manner as before. Collectively, the evidence in Table 5 suggests that information about corporate weather exposure increases stock liquidity.

A positive association between disclosure and liquidity suggests that managers interested in improving liquidity should increase their disclosures to the point where disclosure has no further association with liquidity, which constitutes an equilibrium. We acknowledge that our fixed-effects do not fully control for such endogeneity issues. Yet it is possible that some firms with weather exposure may not be fully disclosing their weather exposure, thus causing some investors to have an information advantage over others. In such cases, withholding disclosure may confer some additional unspecified benefit to managers, which we do not explicitly model. Our point is simply that liquidity benefits could be one reason our measure captures a firm's true weather exposure (see fn. 16).

4.4 Alternative measures

As explained in Sections 1 and 2, we focus on the term *weather* due to its relative objectivity, broad scope, and empirical tractability. Other weather-related terms such as *climate change*, *greenhouse gas*, and *global warming* are politically charged in the current U.S. political climate, which may ultimately reduce their objectivity and even deter companies from using them altogether. Nonetheless, we next test whether our main results are sensitive to including these terms. To do this, we create another measure of weather exposure by summing the frequency count of *weather*, *climate change*, *greenhouse gas*, *carbon dioxide*, and *global warming* for each annual report. We then replicate the cross-sectional and financial outcome tests using the new combination measure in place of the earlier measure. As before, we include firm- and year-fixed effects and other variables.

Table 1, Panel A shows that the average annual report contains about 3.69 weather-related words under this approach, an increase from the 2.53 average for the *weather* measure. Tables 6 and 7 show that all the inferences for the combination measure are similar to those for the previous measure. Some of the economic magnitudes even increase from the previous tests. For example, the combination measure is associated with a larger increase in current and future CAPEX spending and a larger decrease in current and future ROA. We conclude from these findings that our earlier approach is perhaps conservative but nonetheless appropriately captures firms' weather exposures.

5 Conclusion

Prior studies argue that understanding corporate weather exposure is central to contemporary climate research and the design of climate policy (e.g., Hsiang et al., 2017; Nordhaus, 2019). However, recent surveys of climate economics argue that a lack of micro data poses substantial challenges for measuring this construct (e.g., Dell et al., 2014). We therefore create a new and simple measure of corporate weather exposure by applying linguistic analysis techniques to a comprehensive sample of about 100,000 corporate annual reports from 1994 to 2018. In 2018 alone, our sample covers about 4,000 firms, $31 trillion in market value, and 44 million employees, making this one of the largest studies of climate economics. We are not aware of any other regulatory filings that are as comprehensively informative about weather exposure.

We find that over our sample period, our weather exposure measure increases by about 500 percent, which suggests that firms are becoming increasingly exposed to the weather. For 2018, the top quartile of firms most exposed to weather are worth about $9.7 trillion in sum, and our geospatial analysis shows that firms headquartered in the central and southeastern U.S. are currently the most exposed. To validate that our measure proxies for corporate weather exposure, we show that our measure increases in a difference-in-differences manner for firms impacted by hurricanes, correlates well with environmentally dependent firms, and decreases during Republican presidencies when climate regulation is often reduced. We also find significant dollar-value associations for corporate weather exposure by way of additional capital expenditures, reduced profitability, and increased volatility of profits and returns.

Overall, our findings contribute to the ongoing research on climate economics. Future research can conceivably better identify the various demand and supply factors driving a firm's weather exposure, and can also use our measure to construct new dollar-value impacts and long-short trading strategies for weather exposure. Another direction for future work is to apply our measurement technique to other countries.

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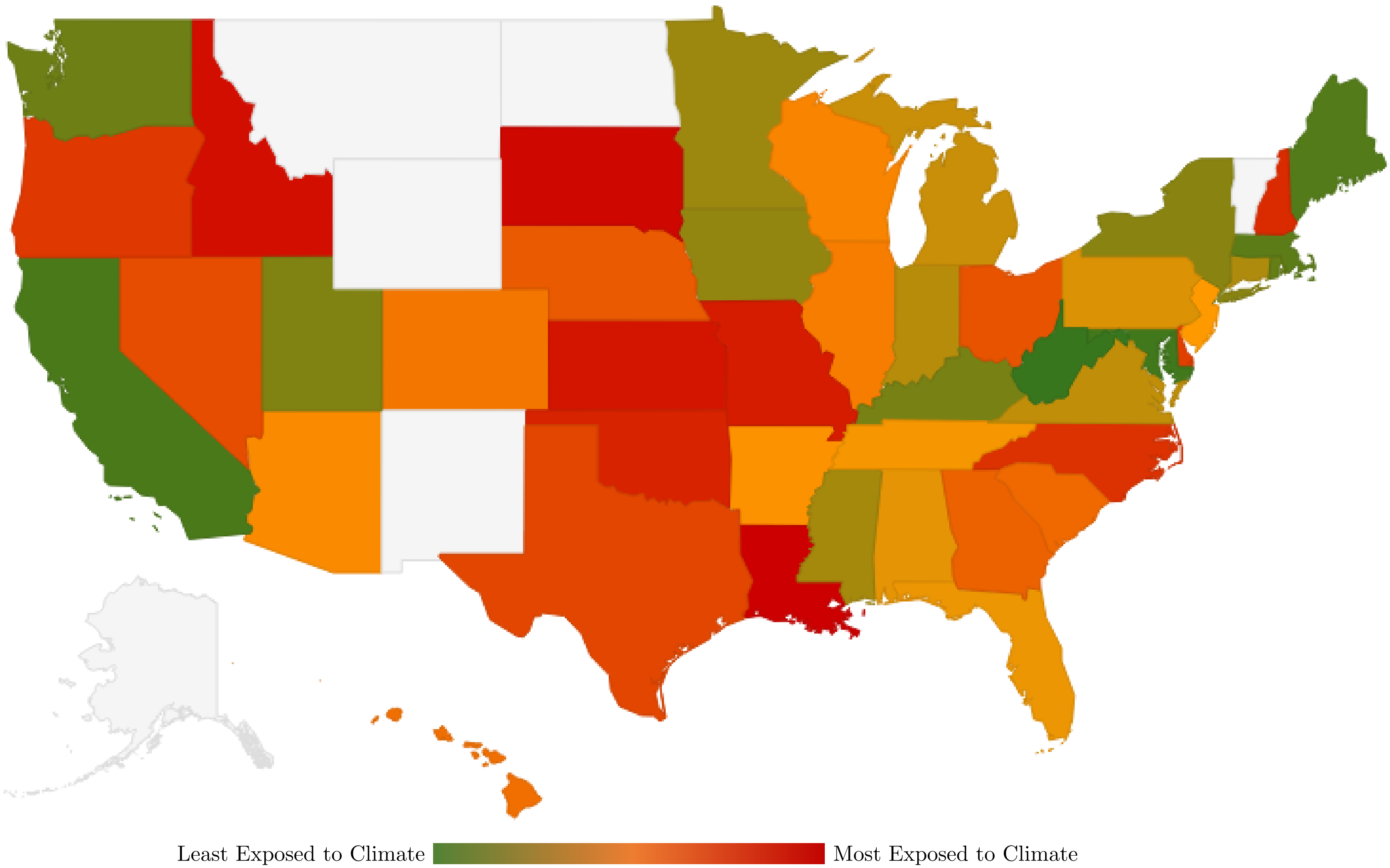
Appendix A
Variable Construction

This table describes each variable used in this study and its source. Index it represents firm i's annual report filing for year t, except where noted. Data source C = Compustat, F = FactSet, NOAA = National Oceanic and Atmospheric Administration, SEC = Securities and Exchange Commission's EDGAR, and WSEC = WRDS SEC Analytics Suite.

Variable	Definition	Source
Weather_{it}	Frequency count of *weather* in the annual report_{it}	SEC
$\text{Climate Change}_{it}$	Frequency count of *climate change* in the annual report_{it}	SEC
$\text{Greenhouse Gas}_{it}$	Frequency count of *greenhouse gas* in the annual report_{it}	SEC
$\text{Carbon Dioxide}_{it}$	Frequency count of *carbon dioxide* in the annual report_{it}	SEC
$\text{Global Warming}_{it}$	Frequency count of *global warming* in the annual report_{it}	SEC
$\sum Weather_{it}$	Weather_{it} + $\text{Climate Change}_{it}$ + $\text{Greenhouse Gas}_{it}$ + $\text{Carbon Dioxide}_{it}$ + $\text{Global Warming}_{it}$	SEC
$\text{Atmospheric CO2}_{t}$	CO_2 reading from the Mauna Loa Observatory (Keeling et al., $1976)_t$	NOAA
$\text{Total Word Count}_{it}$	Total words in the annual report_{it}	WSEC
ROA_{it}	Net income_{it}/total assets_{it}	C
Leverage_{it}	Total debt_{it}/total assets_{it}	C
$\text{Net Cash Flows}_{it}$	Net cash flows_{it}/ total assets_{it}	C
Q_{it}	Market value of firm_{it}/book value of firm_{it}	CRSP, C
CAPEX_{it}	Capital expenditures_{it}/total assets_{it}	C
$\text{R\&D}_{it}$	Research and development_{it}/total assets_{it}	C
$\text{ROA Volatility}_{it=0,1,2}$	Standard deviation of ROA_{it}, ROA_{it+1}, and ROA_{it+2}	C
Returns_{it}	Buy and hold return over the fiscal year of the annual report_{it}	CRSP
$\text{Return Volatility}_{t}$	Standard deviation of daily returns over the fiscal year of the annual report_{it}	CRSP
$\text{Analyst Following}_{it}$	Analyst following averaged over the quarter of the annual report filing date_{it}	IBES
$\text{Institutional Ownership}_{it}$	13F institutional investor ownership at the end of the quarter of the annual report filing date_{it}	F
$\text{Flesch-Kincaid Readability}_{it}$	0.39 × (number of words / number of sentences) + 11.8 × (number of syllables / number of words) – 15.59	WSEC
$\text{Gunning Fog Readability}_{it}$	0.4 × (number of words / number of sentences) + 40 × (number of words with more than two syllables / number of words)	WSEC
$\text{Smog Readability}_{it}$	$1.043 \times \sqrt{30 \times \text{number of words with more than two syllables / number of sentences}} + 3.1291$	WSEC
$\text{Republican President}_{t}$	Indicator variable that equals one in 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2017, and 2018, 0 else_t	-
$\text{Trump Presidency}_{it}$	Indicator variable that equals one in 2017 and 2018, 0 else_t	-
$[0,+N]$ $\text{Percent Spreads}_{it}$	$\left[100 \times \frac{\text{Ask}_{it}-\text{Bid}_{it}}{(\text{Ask}_{it}+\text{Bid}_{it})/2}\right]$, averaged over an N-day window inclusive of the annual report filing date $(t=0)_{it}$	CRSP
$[0,+N]$ $\text{Amihud Illiquidity}_{i}$	$\left[10^6 \times \frac{\lvert\text{Return}_{it}\rvert}{\text{Dollar Trading Volume}_{it}}\right]$, averaged over an N-day window inclusive of the annual report filing date $(t=0)_{it}$	CRSP
$[0,+N]$ $\text{Return Volatility}_{it}$	Standard deviation of daily returns over an N-day window inclusive of the annual report filing date $(t=0)_{it}$	CRSP
$[0,+N]$ $\text{Average Turnover}_{i}$	$\left[\frac{\text{Volume}_{it}}{\text{Shares Outstanding}_{it}}\right]$, averaged over an N-day window inclusive of the annual report filing date $(t=0)_{it}$	CRSP

Figure 1: Heatmap of Corporate Weather Exposure based on Annual Reports from 2018



Using only our most recent data from 2018, we average the *weather* measure for all the firms headquartered in a given state to create an equal-weighted state-level weather exposure measure. Based on a rank order of the state-level measure, firms headquartered in the green states are the least exposed to the weather, and firms headquartered in the red states are the most exposed to the weather. States without five or more public firms are displayed white. See the color gradient above for more detail. The map is robust to including only firms with market values below $2 billion (García and Norli, 2012).

Figure 2: Average Frequency of ‘Weather’ in Annual Reports from 1994 to 2018 by Year

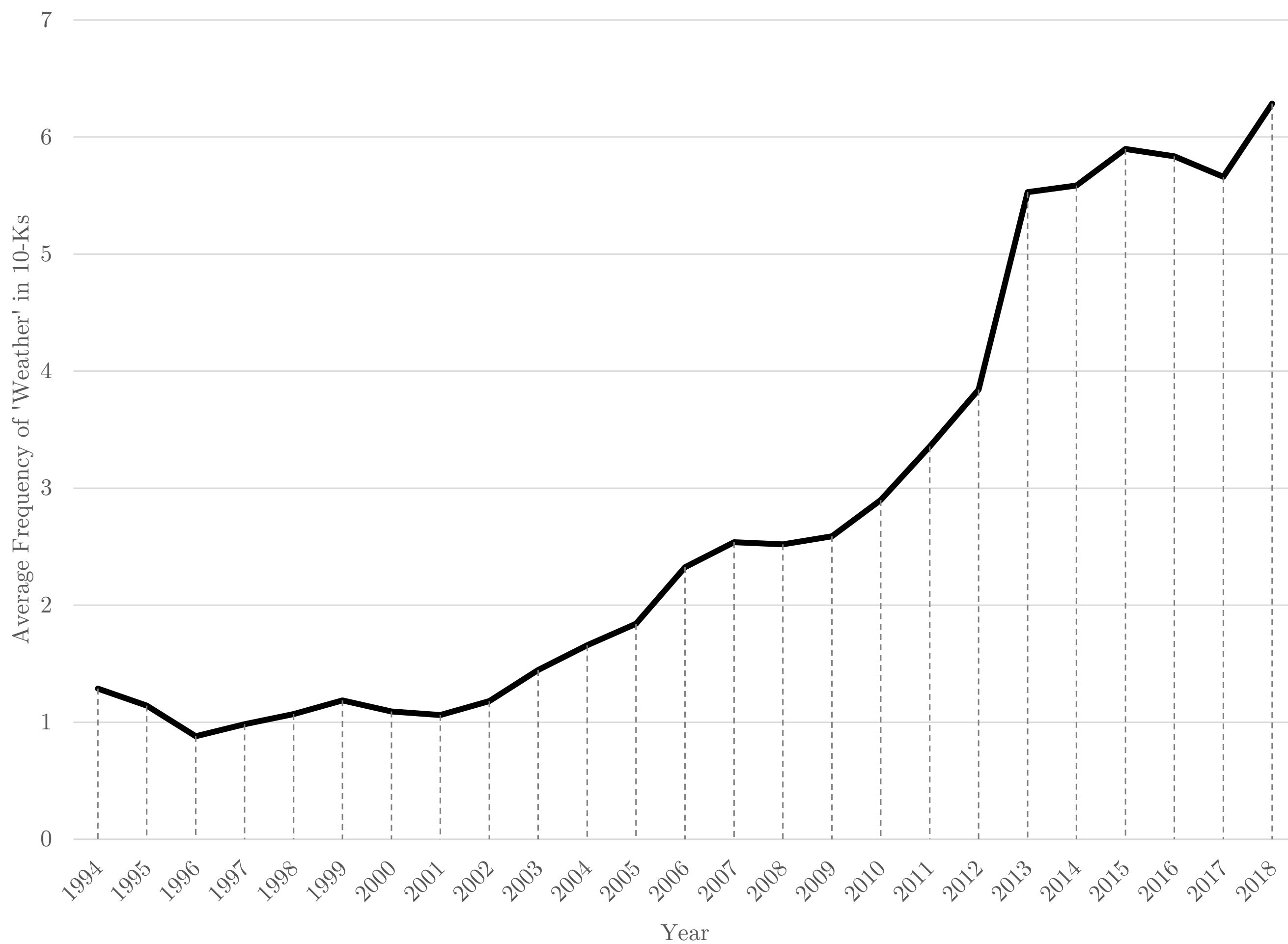


Figure 3: Average Frequency of 'Climate Change' in Annual Reports from 1994 to 2018 by Year

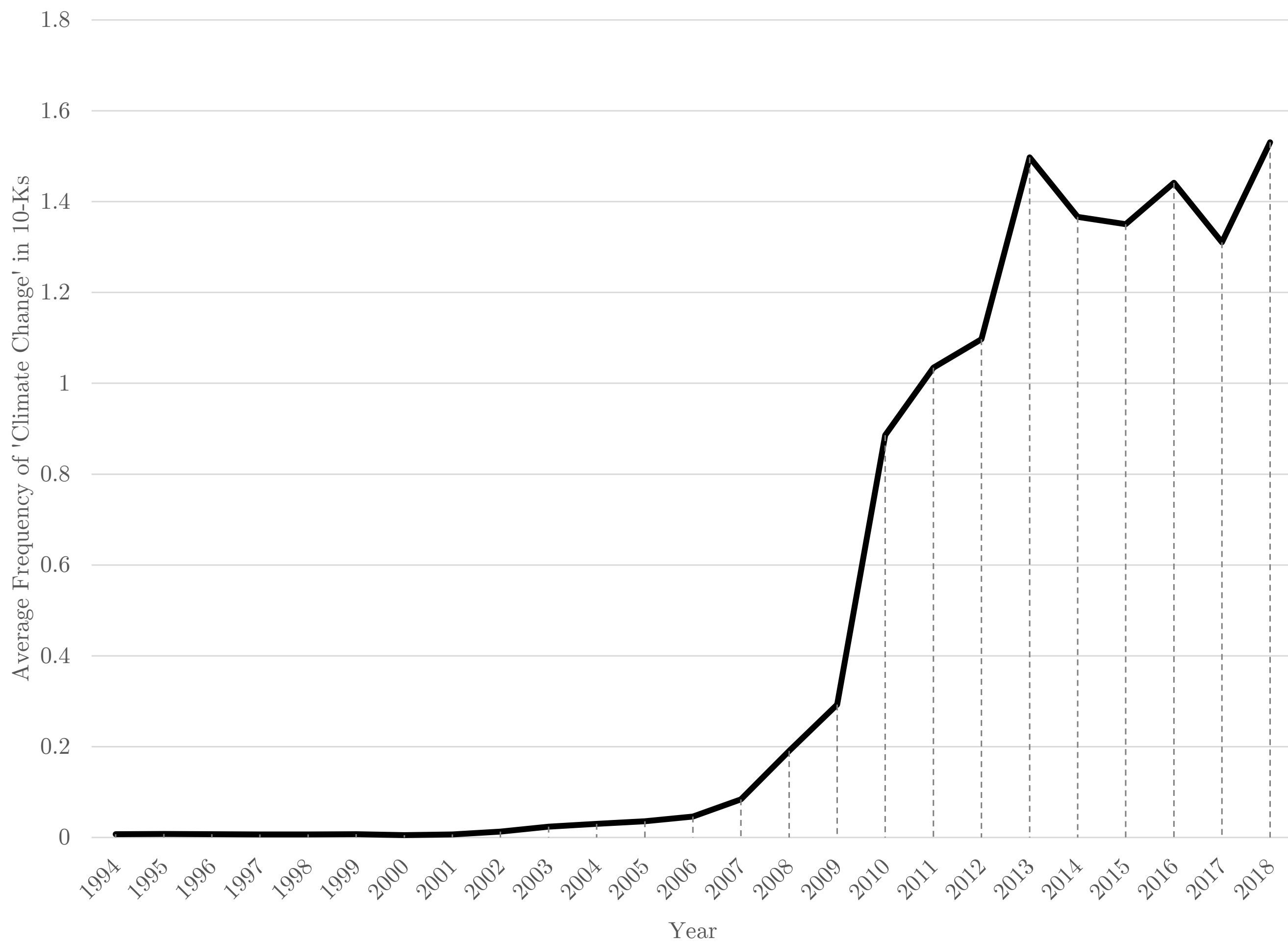


Figure 4: Average Frequency of 'Greenhouse Gas' in Annual Reports from 1994 to 2018 by Year

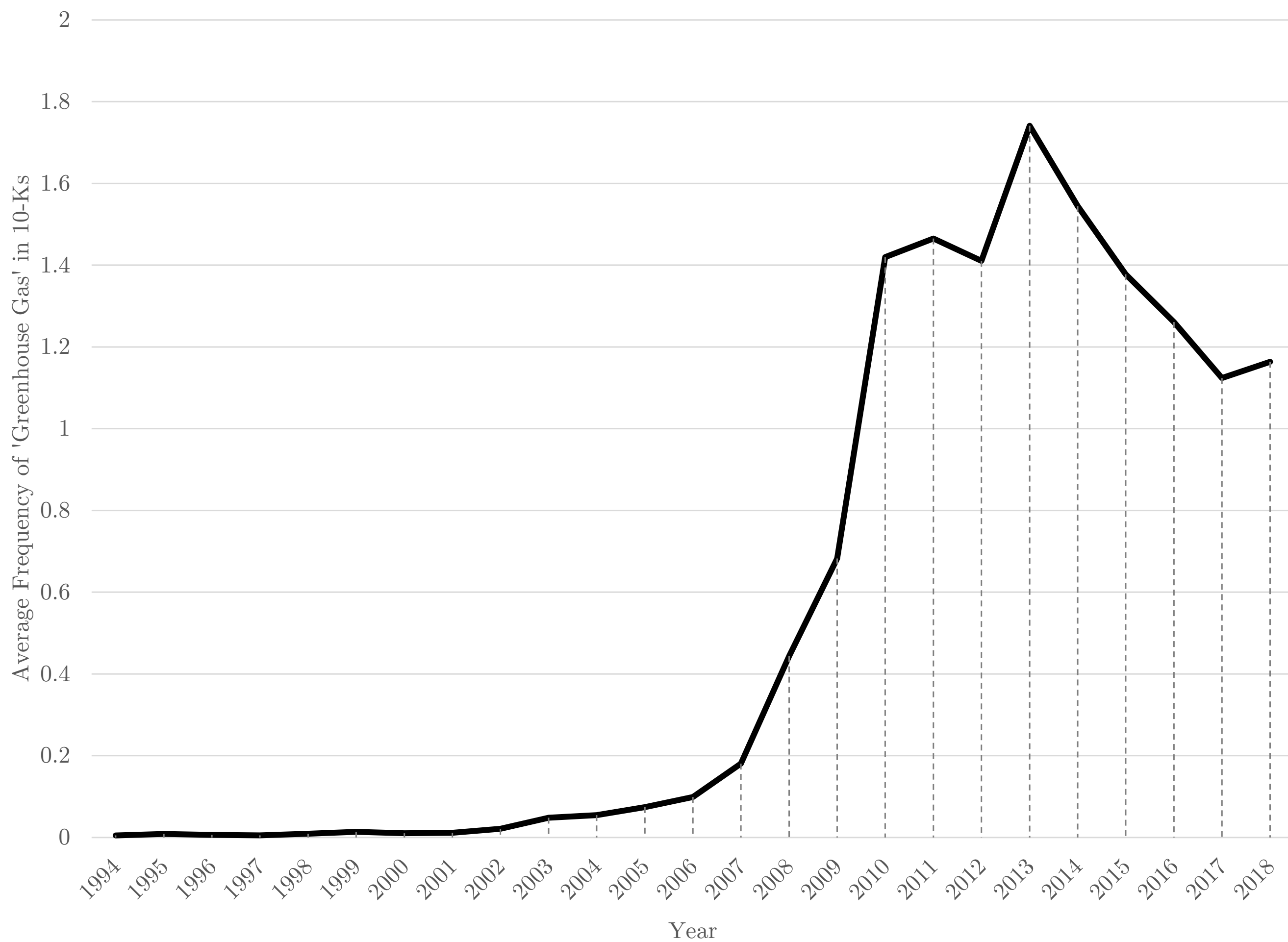


Figure 5: Average Frequency of 'Carbon Dioxide' in Annual Reports from 1994 to 2018 by Year

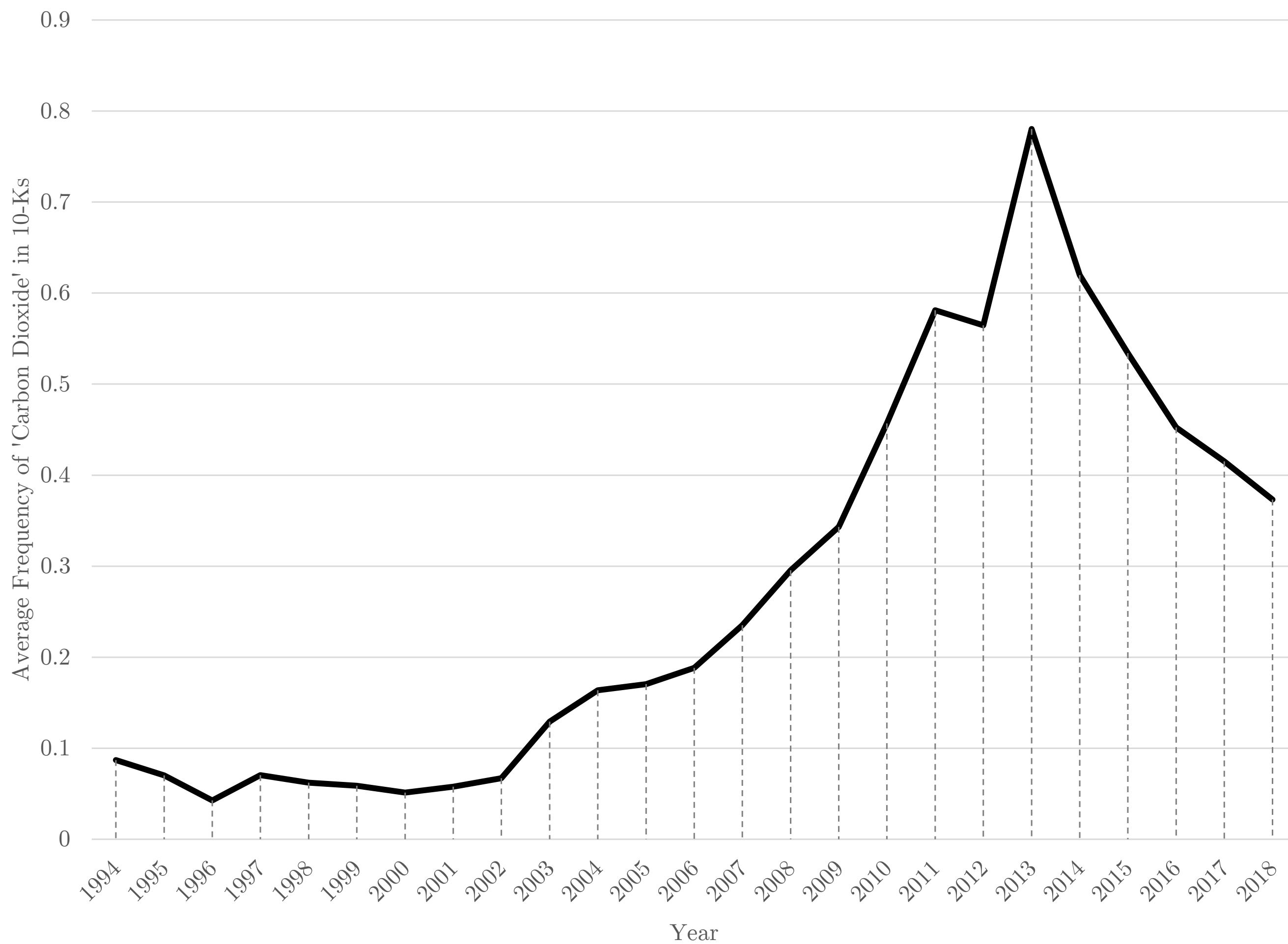


Figure 6: Average Frequency of 'Global Warming' in Annual Reports from 1994 to 2018 by Year

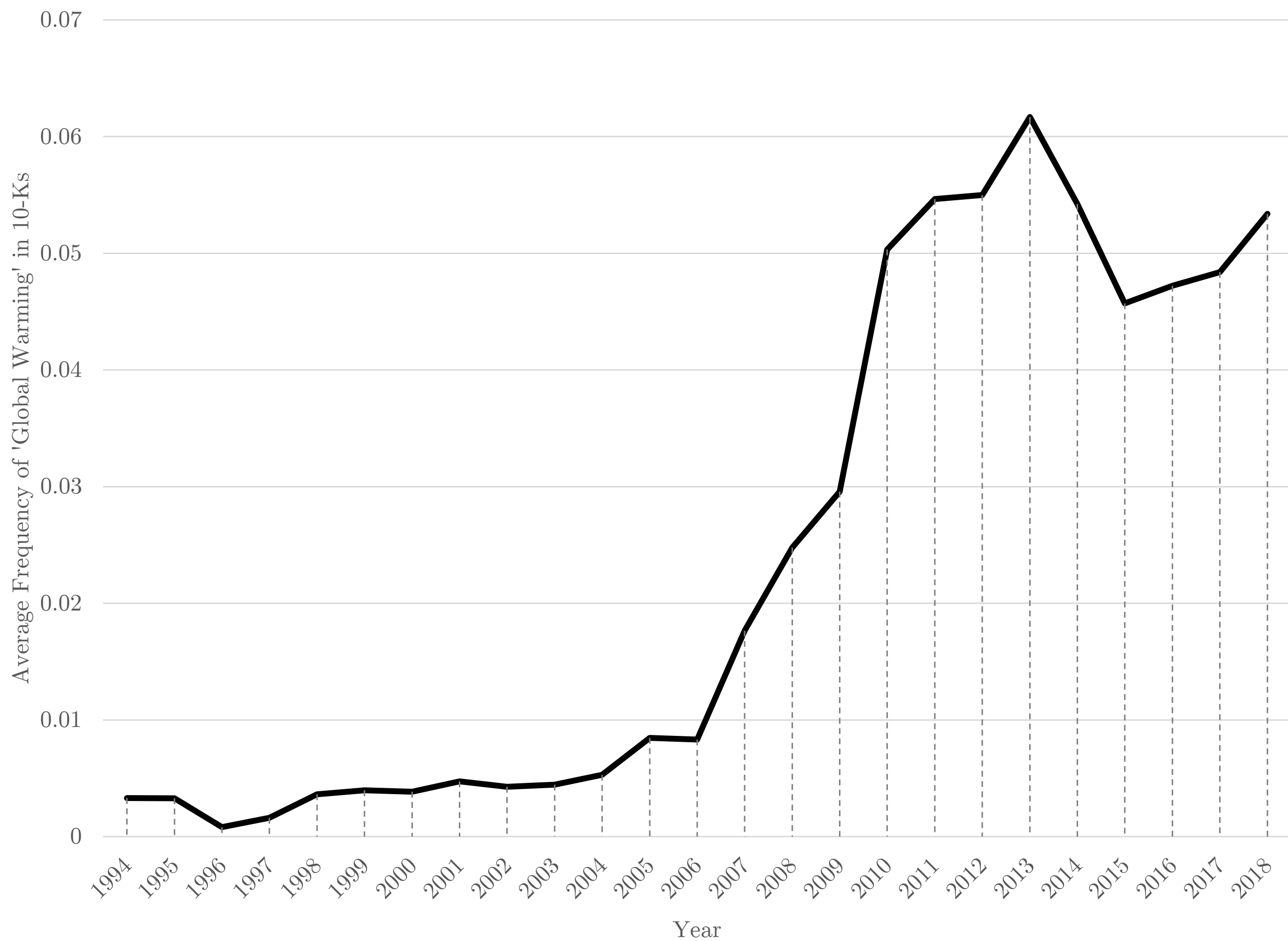


Figure 7: Mauna Loa Atmospheric CO_2 Annual Average from 1994 to 2018
Source: National Oceanic & Atmospheric Administration

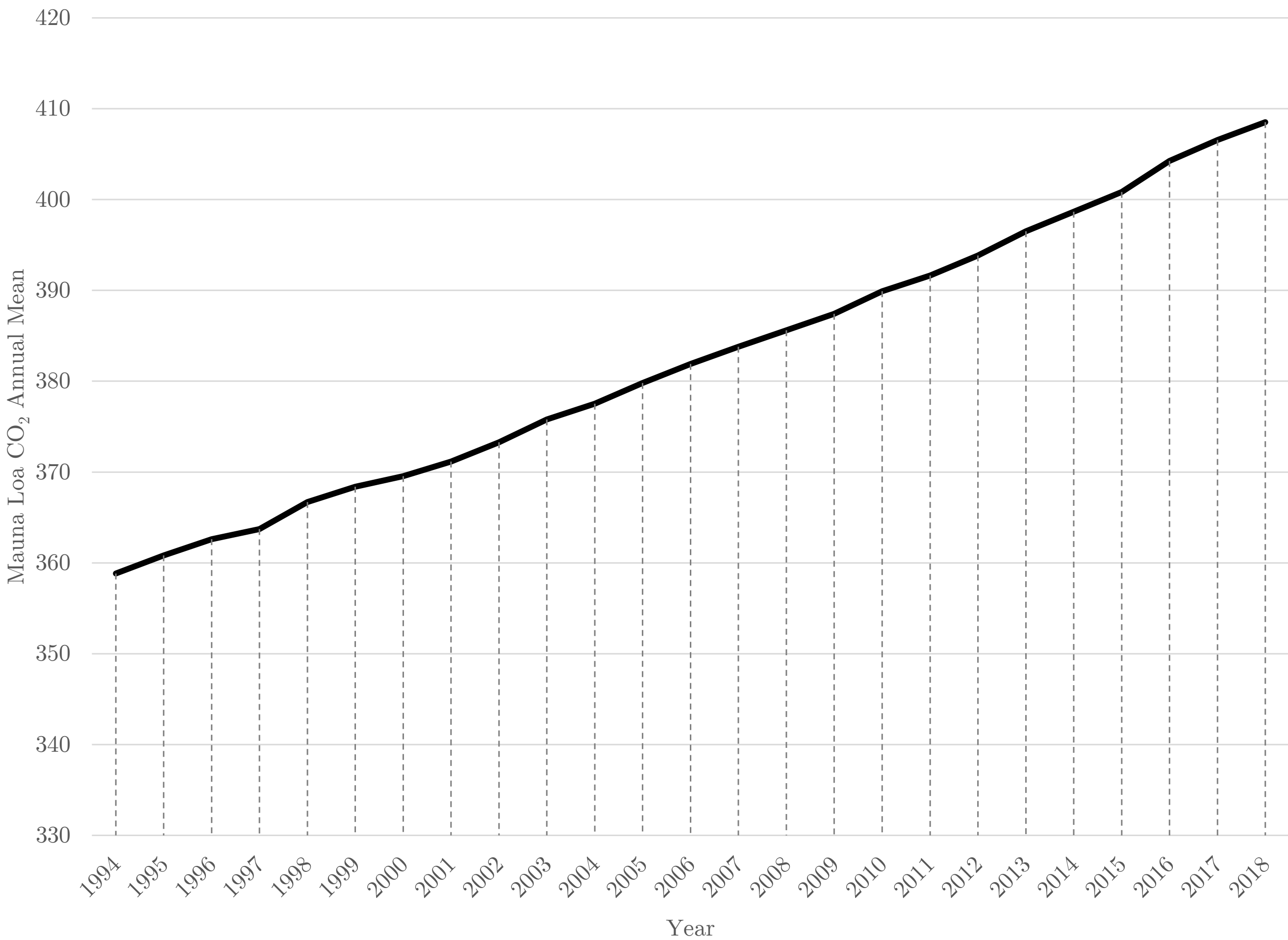


Table 1

Panel A: Descriptive Statistics for Corporate Weather Exposure from 1994 to 2018

Index i represents each firm, and index t represents each year. If necessary, variables are increased by 1 before being (natural) logged. $[0, +N]$ represents the N-day window starting at and including an annual report's filing date. Observations vary based on data availability. Variables are winsorized at the 1% and 99% levels unless a variable has a natural lower bound of zero, in which case it is winsorized from the top only (e.g., Weather$_{it}$). All our inferences are similar when we do not winsorize. See Appendix A for the exact variable definitions.

Variable	N	Mean	σ	P10	P25	P50	P75	P90
Weather$_{it}$	97,402	2.53	6.13	0.00	0.00	0.00	2.00	7.00
Climate Change$_{it}$	97,402	0.46	1.62	0.00	0.00	0.00	0.00	1.00
Greenhouse Gas$_{it}$	97,402	0.48	2.06	0.00	0.00	0.00	0.00	0.00
Carbon Dioxide$_{it}$	97,402	0.19	0.81	0.00	0.00	0.00	0.00	0.00
Global Warming$_{it}$	97,402	0.03	0.16	0.00	0.00	0.00	0.00	0.00
$\sum Weather_{it}$	97,402	3.69	8.87	0.00	0.00	0.00	3.00	10.00
Total Word Count$_{it}$	97,402	39996.89	24152.63	15758.00	23451.00	34897.00	50022.00	68874.00
Log(Total Assets)$_{it}$	97,402	6.31	2.08	3.59	4.79	6.27	7.70	9.07
ROA$_{it}$	97,402	-0.04	0.24	-0.25	-0.02	0.02	0.06	0.11
Leverage$_{it}$	97,402	0.23	0.32	0.00	0.03	0.18	0.36	0.54
Net Cash Flows$_{it}$	97,402	0.00	0.20	-0.08	-0.01	0.00	0.03	0.10
Q$_{it}$	97,402	1.36	1.67	0.14	0.37	0.83	1.65	3.12
CAPEX$_{it}$	97,402	0.04	0.06	0.00	0.01	0.02	0.06	0.10
R&D$_{it}$	97,402	0.05	0.11	0.00	0.00	0.00	0.04	0.15
Returns$_{it}$	97,402	0.13	0.62	-0.51	-0.23	0.05	0.33	0.75
Return Volatility$_{it}$	97,402	0.03	0.02	0.01	0.02	0.03	0.04	0.06
Analyst Following$_{it}$	97,402	4.14	5.04	0.00	0.00	2.26	5.94	11.26
Institutional Ownership$_{it}$	97,402	0.45	0.34	0.00	0.10	0.44	0.76	0.93
Flesch-Kincaid Readability$_{it}$	97,402	15.75	1.31	14.44	15.06	15.69	16.34	17.01
Gunning Fog Readability$_{it}$	97,402	20.00	1.33	18.67	19.30	19.94	20.61	21.32
Smog Readability$_{it}$	97,402	17.38	0.83	16.42	16.88	17.35	17.83	18.33
ROA Volatility$_{it=0,1,2}$	76,305	0.06	0.11	0.00	0.01	0.02	0.07	0.17
$[0, +3]$ Average Percent Spread$_{it}$	95,771	1.52	2.58	0.04	0.10	0.45	1.79	4.22
$[0, +3]$ Average Amihud$_{it}$	96,575	1.23	5.62	0.00	0.00	0.01	0.15	1.31
$[0, +3]$ Return Volatility$_{it}$	96,741	0.03	0.03	0.01	0.01	0.02	0.04	0.07
$[0, +3]$ Average Turnover$_{it}$	96,783	0.01	0.01	0.00	0.00	0.00	0.01	0.02
$[0, +3]$ Returns$^2_{it}$	96,777	0.01	0.02	0.00	0.00	0.00	0.00	0.02
$[0, +30]$ Average Percent Spread$_{it}$	96,363	1.54	2.58	0.04	0.11	0.47	1.86	4.25
$[0, +30]$ Average Amihud$_{it}$	96,786	1.80	8.14	0.00	0.00	0.01	0.19	1.97
$[0, +30]$ Return Volatility$_{it}$	96,765	0.03	0.03	0.01	0.02	0.02	0.04	0.06
$[0, +30]$ Average Turnover$_{it}$	96,793	0.01	0.01	0.00	0.00	0.00	0.01	0.02
$[0, +30]$ Returns$^2_{it}$	96,793	0.02	0.06	0.00	0.00	0.00	0.02	0.06

Table 1

Panel B: Correlations for Corporate Weather Exposure from 1994 to 2018

This table presents Pearson correlations for the corporate weather exposure measures. See Appendix A for the exact variable definitions. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	Weather_{it}	$\text{Climate Change}_{it}$	$\text{Greenhouse Gas}_{it}$	$\text{Carbon Dioxide}_{it}$	$\text{Global Warming}_{it}$
Weather_{it}	1.00				
$\text{Climate Change}_{it}$	0.50^{***}	1.00			
$\text{Greenhouse Gas}_{it}$	0.43^{***}	0.63^{***}	1.00		
$\text{Carbon Dioxide}_{it}$	0.39^{***}	0.50^{***}	0.63^{***}	1.00	
$\text{Global Warming}_{it}$	0.26^{***}	0.37^{***}	0.39^{***}	0.31^{***}	1.00

Table 2

Corporate Weather Exposure Cross-Sectional Analysis from 1994 to 2018

Index i represents each firm, and index t represents each year. The dependent variables represent the frequency count of the corresponding term in firm i's annual report for year t. See Appendix A for the exact variable definitions. The number of observations increases in columns 5 and 6 due to the removal of firm-fixed effects. Standard errors are in parentheses and clustered two-way as denoted in the table. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) Log(Weather)$_{it}$	(2) Log(Weather)$_{it}$	(3) Log(Weather)$_{it}$	(4) Log(Weather)$_{it}$	(5) Log(Weather)$_{it}$	(6) Log(Weather)$_{it}$
Utility Firm$_i$	1.930***					
	(0.060)					
Oil, Gas, or Coal Firm$_i$	0.920***					
	(0.056)					
Food, Tobacco, or Textile Firm$_i$	0.377***					
	(0.054)					
Financial Services Firm$_i$	-0.346***					
	(0.023)					
Healthcare Firm$_i$	-0.437***					
	(0.037)					
Atmospheric CO2$_t$		0.012***				
		(0.001)				
Republican President$_t$			-0.043***			
			(0.011)			
Trump Presidency$_t$				-0.024***		
				(0.008)		
Log(Total Assets)$_{it}$	0.061***	0.050***	0.051***	0.032**	0.120***	0.050***
	(0.005)	(0.007)	(0.007)	(0.015)	(0.008)	(0.007)
Log(Total Word Count)$_{it}$	0.161***	0.113***	0.117***	0.175***	0.250***	0.122***
	(0.025)	(0.014)	(0.012)	(0.040)	(0.026)	(0.012)
Flesch-Kincaid Readability$_{it}$	-0.078**	0.071**	0.059**	-0.110**	0.145***	0.070**
	(0.029)	(0.028)	(0.028)	(0.049)	(0.039)	(0.029)
Gunning Fog Readability$_{it}$	0.129***	-0.075**	-0.058*	0.136	-0.149***	-0.068**
	(0.033)	(0.031)	(0.031)	(0.106)	(0.047)	(0.032)
Smog Readability$_{it}$	-0.144***	0.002	-0.014	-0.094	-0.005	-0.015
	(0.027)	(0.015)	(0.014)	(0.125)	(0.033)	(0.015)
Sample	1994–2018	1994–2018	1994–2018	2016–2018	1994–2018	1994–2018
Firm-Fixed Effects	N	Y	Y	Y	Y	Y
Year-Fixed Effects	Y	N	N	N	N	Y
Time Trend	N	N	Y	Y	N	N
Two-Way Clustering	Firm, Year	Firm, Year	Firm, Year	Firm	Firm, Year	Firm, Year
Observations	97,402	97,402	97,402	13,576	97,402	97,402
R^2	0.37	0.85	0.85	0.97	0.84	0.85

Table 3
Difference-in-Differences Quasi-Experiments for Corporate Weather Exposure from 1994 to 2018

Index i represents each firm, and index t represents each year. The dependent variables represent the frequency count of the corresponding term in firm i's annual report for year t. See Appendix A for the exact variable definitions. Standard errors are in parentheses. Due to the short-window research design, we appropriately use one-way clustered standard errors. Recall that Hurricane Katrina hit in 2005, and Hurricane Sandy hit in 2012. We do not include the interacting state variables as main effects since they are firm-invariant and subsumed by the firm-fixed effects. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) Log(Weather)$_{it}$	(2) Log(Weather)$_{it}$
Post Katrina$_i$	0.088***	
	(0.007)	
Post Katrina × AL, FL, LA, or MS Firm$_{it}$	0.111***	
	(0.033)	
Post Sandy$_i$		0.050***
		(0.005)
Post Sandy × CT, DE, MA, ME, NH, NJ, NY, RI, or VT Firm$_{it}$		0.027***
		(0.010)
Log(Total Assets)$_{it}$	0.045***	0.041***
	(0.012)	(0.009)
Log(Total Word Count)$_{it}$	0.118***	0.068***
	(0.023)	(0.016)
Sample	2004–2007	2011–2014
Firm-Fixed Effects	Y	Y
Readability Controls	Y	Y
Clustering	Firm	Firm
Observations	17,305	15,603
R^2	0.92	0.96

Table 4
Corporate Weather Exposure, Capital Expenditures, Profitability, and Volatility from 1994 to 2018
Index i represents each firm, and index t represents each year. See Appendix A for the exact variable definitions. Standard errors are in parentheses and standard errors are clustered two-way as denoted in the table. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) CAPEX_{it}	(2) CAPEX_{it+1}	(3) CAPEX_{it+2}	(4) ROA_{it}	(5) ROA_{it+1}	(6) ROA_{it+2}	(7) ROA $\text{Volatility}_{it=0,1,2}$	(8) Return Volatility_{it+1}
Log(Weather)_{it}	0.0018***	0.0020***	0.0010*	-0.0030**	-0.0049***	-0.0031**	0.0029***	0.0006***
	(0.00053)	(0.00055)	(0.00055)	(0.00134)	(0.00155)	(0.00159)	(0.00100)	(0.00015)
Net Cash Flows_{it}	-0.0127***	0.0017	0.0033***	0.0895***	0.0146*	0.0017	0.0136***	0.0004
	(0.00192)	(0.00106)	(0.00110)	(0.01914)	(0.00826)	(0.01056)	(0.00408)	(0.00059)
Q_{it}	0.0043***	0.0038***	0.0021***	0.0066***	0.0087***	0.0010	0.0025*	0.0002
	(0.00030)	(0.00026)	(0.00030)	(0.00140)	(0.00151)	(0.00157)	(0.00124)	(0.00027)
$\text{Log(Total Assets)}_{it}$	0.0015***	-0.0003	-0.0030***	0.0347***	-0.0112***	-0.0238***	0.0065**	-0.0003
	(0.00053)	(0.00053)	(0.00053)	(0.00232)	(0.00251)	(0.00243)	(0.00257)	(0.00036)
$\text{R\&D}_{it}$	0.0303***	0.0105**	0.0065	-1.2440***	-0.4179***	-0.2176***	-0.0460*	0.0033
	(0.00469)	(0.00448)	(0.00491)	(0.03060)	(0.03656)	(0.03875)	(0.02430)	(0.00203)
CAPEX_{it}				0.0645***	0.0882***	0.0509*	0.0235	0.0047
				(0.02394)	(0.02582)	(0.02698)	(0.01859)	(0.00317)
ROA_{it}	0.0040*	0.0133***	0.0087***				-0.1975***	-0.0082***
	(0.00220)	(0.00182)	(0.00177)				(0.01947)	(0.00086)
Leverage_{it}	-0.0016	-0.0109***	-0.0080***	-0.0635***	0.0043	0.0277***	-0.0100	0.0026**
	(0.00134)	(0.00260)	(0.00214)	(0.02101)	(0.00843)	(0.00815)	(0.00687)	(0.00095)
Returns_{it}	-0.0039***	0.0028***	0.0033***	0.0322***	0.0368***	0.0103***	-0.0040**	-0.0022***
	(0.00049)	(0.00050)	(0.00050)	(0.00119)	(0.00132)	(0.00150)	(0.00180)	(0.00055)
Return Volatility_{it}	-0.0801***	-0.1017***	-0.0585**	-2.4579***	-1.1472***	-0.5363***	0.4564***	0.3532***
	(0.02196)	(0.01895)	(0.02303)	(0.07894)	(0.08213)	(0.08216)	(0.07889)	(0.02041)
$\text{Log(Total Word Count)}_{it}$	-0.0009	-0.0000	-0.0001	-0.0315***	-0.0115***	-0.0002	0.0020	0.0007**
	(0.00060)	(0.00060)	(0.00063)	(0.00226)	(0.00228)	(0.00216)	(0.00124)	(0.00026)
Sample	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018
Firm-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Readability Controls	Y	Y	Y	Y	Y	Y	Y	Y
Two-Way Clustering	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	97,402	85,420	75,205	97,402	85,420	75,203	75,184	85,366
R^2	0.71	0.72	0.72	0.75	0.66	0.65	0.65	0.74

Table 5
Corporate Weather Exposure and Stock Liquidity from 1994 to 2018

Index i represents each firm, and index t represents each year. $[0, +3$ days$]$ and $[0, +30$ days$]$ represent windows starting at and including an annual report's filing date. Observations vary based on data availability. See Appendix A for the exact variable definitions. Decreased spreads and decreased Amihud both signify increased stock liquidity. Standard errors are in parentheses and standard errors are clustered two-way as denoted in the table. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) $[0, +3]$ Average Percent Spread$_{it}$	(2) $[0, +3]$ Average Amihud$_{it}$	(3) $[0, +30]$ Average Percent Spread$_{it}$	(4) $[0, +30]$ Average Amihud$_{it}$
Log(Weather)$_{it}$	-0.063**	-0.183***	-0.071**	-0.286***
	(0.030)	(0.052)	(0.032)	(0.067)
$[0, +3]$ Return Volatility$_{it}$	18.650***	38.579***		
	(1.214)	(3.477)		
$[0, +3]$ Average Turnover$_{it}$	-47.755***	-83.610***		
	(3.794)	(8.262)		
$[0, +3]$ Returns$^2_{it}$	-1.861*	-14.073***		
	(1.084)	(2.452)		
$[0, +30]$ Return Volatility$_{it}$			32.152***	87.384***
			(2.564)	(6.920)
$[0, +30]$ Average Turnover$_{it}$			-66.413***	-166.376***
			(5.035)	(16.581)
$[0, +30]$ Returns$^2_{it}$			-2.696***	-10.486***
			(0.196)	(1.146)
Log(Total Assets)$_{it}$	-0.297***	-0.529***	-0.275***	-0.824***
	(0.041)	(0.122)	(0.039)	(0.189)
ROA$_{it}$	0.009	0.025	0.008	0.046
	(0.015)	(0.032)	(0.012)	(0.041)
Leverage$_{it}$	0.364***	0.691***	0.256***	0.732**
	(0.098)	(0.145)	(0.084)	(0.283)
Returns$_{it}$	-0.448***	-0.548***	-0.383***	-0.641***
	(0.065)	(0.047)	(0.073)	(0.099)
Return Volatility$_{it}$	28.952***	51.041***	23.105***	63.767***
	(2.514)	(4.342)	(2.191)	(6.321)
Analyst Following$_{it}$	0.027***	0.054***	0.031***	0.069***
	(0.006)	(0.013)	(0.007)	(0.018)
Institutional Ownership$_{it}$	-0.110	0.228*	-0.080	0.331*
	(0.065)	(0.115)	(0.073)	(0.173)
Log(Total Word Count)$_{it}$	0.030	-0.161*	0.019	-0.236**
	(0.035)	(0.083)	(0.031)	(0.105)
Sample	1994–2018	1994–2018	1994–2018	1994–2018
Firm-Fixed Effects	Y	Y	Y	Y
Year-Fixed Effects	Y	Y	Y	Y
Readability Controls	Y	Y	Y	Y
Two-Way Clustering	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	95,632	96,461	96,259	96,694
R^2	0.71	0.44	0.75	0.49

Table 6
Corporate Weather Exposure Cross-Sectional Robustness Analysis from 1994 to 2018
Index i represents each firm, and index t represents each year. The dependent variables represent the frequency count of the corresponding term in firm i's annual report for year t. See Appendix A for the exact variable definitions. The number of observations increases in columns 5 and 6 due to the removal of firm-fixed effects. Standard errors are in parentheses and clustered two-way as denoted in the table. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) Log($\sum Weather_{it}$)	(2) Log($\sum Weather_{it}$)	(3) Log($\sum Weather_{it}$)	(4) Log($\sum Weather_{it}$)	(5) Log($\sum Weather_{it}$)	(6) Log($\sum Weather_{it}$)
Utility Firm$_i$	2.052***					
	(0.059)					
Oil, Gas, or Coal Firm$_i$	1.310***					
	(0.095)					
Food, Tobacco, or Textile Firm$_i$	0.346***					
	(0.052)					
Financial Services Firm$_i$	-0.422***					
	(0.030)					
Healthcare Firm$_i$	-0.496***					
	(0.054)					
Atmospheric CO2$_t$		0.018***				
		(0.001)				
Republican President$_t$			-0.110***			
			(0.016)			
Trump Presidency$_t$				-0.020**		
				(0.008)		
Log(Total Assets)$_{it}$	0.077***	0.059***	0.063***	0.035**	0.167***	0.064***
	(0.007)	(0.009)	(0.009)	(0.016)	(0.011)	(0.009)
Log(Total Word Count)$_{it}$	0.200***	0.099***	0.111***	0.164***	0.310***	0.130***
	(0.029)	(0.017)	(0.013)	(0.037)	(0.037)	(0.014)
Flesch-Kincaid Readability$_{it}$	-0.060*	0.107***	0.089**	-0.142**	0.222***	0.090***
	(0.032)	(0.037)	(0.034)	(0.058)	(0.054)	(0.031)
Gunning Fog Readability$_{it}$	0.124***	-0.114**	-0.084**	0.157	-0.227***	-0.083**
	(0.035)	(0.042)	(0.038)	(0.117)	(0.067)	(0.034)
Smog Readability$_{it}$	-0.175***	0.011	-0.022	-0.073	0.000	-0.028*
	(0.028)	(0.022)	(0.017)	(0.133)	(0.046)	(0.016)
Sample	1994–2018	1994–2018	1994–2018	2016–2018	1994–2018	1994–2018
Firm-Fixed Effects	N	Y	Y	Y	Y	Y
Year-Fixed Effects	Y	N	N	N	N	Y
Time Trend	N	N	Y	Y	N	N
Two-Way Clustering	Firm, Year	Firm, Year	Firm, Year	Firm	Firm, Year	Firm, Year
Observations	97,402	97,402	97,402	13,576	97,402	97,402
R^2	0.42	0.85	0.85	0.98	0.83	0.85

Table 7

Corporate Weather Exposure, Capital Expenditures, Profitability, and Volatility Robustness Analysis from 1994 to 2018

Index i represents each firm, and index t represents each year. See Appendix A for the exact variable definitions. Standard errors are in parentheses and standard errors are clustered two-way as denoted in the table. ***, **, and * indicate statistical significance at the two-tailed 1%, 5%, and 10% level, respectively.

	(1) CAPEX_{it}	(2) CAPEX_{it+1}	(3) CAPEX_{it+2}	(4) ROA_{it}	(5) ROA_{it+1}	(6) ROA_{it+2}	(7) ROA $\text{Volatility}_{it=0,1,2}$	(8) Return Volatility_{it+1}
$\text{Log}(\sum Weather_{it})$	0.0016***	0.0018***	0.0011*	-0.0044***	-0.0049***	-0.0037**	0.0022**	0.0005***
	(0.00056)	(0.00053)	(0.00054)	(0.00126)	(0.00144)	(0.00151)	(0.00100)	(0.00016)
Net Cash Flows_{it}	-0.0127***	0.0017	0.0033***	0.0895***	0.0146*	0.0017	0.0136***	0.0004
	(0.00192)	(0.00105)	(0.00110)	(0.01915)	(0.00825)	(0.01056)	(0.00408)	(0.00059)
Q_{it}	0.0043***	0.0038***	0.0021***	0.0067***	0.0087***	0.0011	0.0025*	0.0002
	(0.00030)	(0.00026)	(0.00030)	(0.00140)	(0.00151)	(0.00157)	(0.00124)	(0.00027)
$\text{Log(Total Assets)}_{it}$	0.0015***	-0.0004	-0.0030***	0.0348***	-0.0111***	-0.0237***	0.0065**	-0.0003
	(0.00053)	(0.00053)	(0.00053)	(0.00233)	(0.00251)	(0.00243)	(0.00257)	(0.00036)
$\text{R\&D}_{it}$	0.0303***	0.0105**	0.0065	-1.2439***	-0.4179***	-0.2175***	-0.0459*	0.0034
	(0.00470)	(0.00448)	(0.00491)	(0.03060)	(0.03656)	(0.03875)	(0.02430)	(0.00203)
CAPEX_{it}				0.0650***	0.0884***	0.0514*	0.0235	0.0047
				(0.02394)	(0.02583)	(0.02701)	(0.01858)	(0.00318)
ROA_{it}	0.0041*	0.0133***	0.0088***				-0.1975***	-0.0082***
	(0.00220)	(0.00182)	(0.00177)				(0.01948)	(0.00086)
Leverage_{it}	-0.0016	-0.0109***	-0.0080***	-0.0635***	0.0043	0.0277***	-0.0100	0.0026**
	(0.00134)	(0.00260)	(0.00214)	(0.02102)	(0.00843)	(0.00814)	(0.00687)	(0.00095)
Returns_{it}	-0.0039***	0.0028***	0.0033***	0.0322***	0.0368***	0.0103***	-0.0040**	-0.0022***
	(0.00049)	(0.00050)	(0.00050)	(0.00119)	(0.00132)	(0.00150)	(0.00180)	(0.00055)
Return Volatility_{it}	-0.0800***	-0.1016***	-0.0586**	-2.4560***	-1.1466***	-0.5352***	0.4572***	0.3533***
	(0.02205)	(0.01897)	(0.02291)	(0.07881)	(0.08203)	(0.08205)	(0.07876)	(0.02039)
$\text{Log(Total Word Count)}_{it}$	-0.0009	-0.0000	-0.0001	-0.0313***	-0.0114***	-0.0001	0.0021	0.0007**
	(0.00061)	(0.00060)	(0.00064)	(0.00225)	(0.00228)	(0.00215)	(0.00124)	(0.00025)
Sample	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018	1994–2018
Firm-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Year-Fixed Effects	Y	Y	Y	Y	Y	Y	Y	Y
Readability Controls	Y	Y	Y	Y	Y	Y	Y	Y
Two-Way Clustering	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Observations	97,402	85,420	75,205	97,402	85,420	75,203	75,184	85,366
R^2	0.71	0.72	0.72	0.75	0.66	0.65	0.65	0.74