ESG Sentiment and Climate Change: An Analysis of the Effects of Climate Disaster Exposure on ESG Reports

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Data, Code and Appendix: https://github.com/lschreiber9/Climate-Sentiment

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Introduction

ESG is central to discussions surrounding the role of firms with respect to combating climate change. It has become common for companies around the world to communicate ESG activities by publishing annual reports. The literature has increasingly begun to study the drivers of ESG reporting and activities. Companies are able to communicate risks, easing investor concerns which directly affects risk premia and overall financial performance [1-3] and reports act as signaling mechanisms to inform investors [4]. ESG scores published by major institutions are not transparent and sensitive to alternative weighting [5] hence the use of alternative measures, namely the usage of Natural Language Processing has become a well-known practice in estimating ESG sentiment [6-10]. In our project we will study the impacts of climate disaster exposure on the reporting language and content of ESG reports. We find limited evidence that climate disasters cause firms to report more on the opportunities arising from climate change and ultimately no systematic explanation for differing reactions to disasters.

Firm Level Data

We restrict our sample to industrial firms, the so-called XLI Components, in the S&P 500 and their corresponding ESG reports for the years 2021-2023. The index combines numerous industries, including for instance aerospace, defense, construction, or commercial services. Furthermore we will restrict our study to firms which are headquartered in the U.S. and which are independent.

Full list of companies available at: https://www.sectorspdrs.com/mainfund/xli

Project-Roadmap

Our project is composed of three parts. First, we compute a Sentiment Index, ranging from -5 to 5, for all ESG Reports using a NLP model. Then, we will employ a simple staggered Differences-in-differences to estimate the causal relationship between disaster exposure and ESG Sentiment. Finally we use web scraping to analyze the exposure to climate disasters at the firm and state level based on news headlines.

The NPL Analysis

We fine-tune an existing BERT model with the expert annotated dataset from [8] to analyze the text of the ESG-Reports we collected. The model classifies sentiment into Risk, Opportunity, or Neutral, providing insights into how organizations communicate about climate topics.

Classification Criteria:

1. A text is classified as "**Risk**" if it focuses on:
   - Business downside risks, potential losses, or adverse developments.
   - Negative impacts of activities on society or the environment.
2. A text is classified as "**Opportunity**" if it emphasizes:
   - Business opportunities from climate change mitigation or adaptation.
   - Positive impacts of activities on society or the environment.
3. Neutral A text is classified as "**Neutral**" if it:
   - States facts or developments without positive or negative framing.
   - Lacks specific adjectives that indicate risk or opportunity.

We keep only climate relevant paragraphs from every ESG-Report by implementing a key word analysis. The list of key words is from [8]. Our final dataset for the NLP analysis contains 13,959 paragraphs.

The Sentiment Index

Some steps were considered in the code for the Index creation:

1. Training the BERT model
2. Creating the ESG-Reports Dataset
3. Sentiment Score from the climate_sentiment_model

Estimation Strategy

Background

There is strong evidence for the effect on climate change on weather extremes and resulting damages will affect firms both in the short and long-run [11-13]. In order to study the impacts of climate disasters we need to measure firm disaster exposure. We define exposure to climate disasters as having headquarters within or neighboring a county that is affected by a climate disaster. Including the neighboring county allows us to capture some of the spillover effects caused by such catastrophes.

The data on whether or not a county is affected comes from the FEMA disaster declaration database where we take only major emergencies into account. The FEMA will declare emergency at the county level in the case of active danger meaning companies and workers will be truly exposed. Furthermore we collect data on the CEOs educational background and control for climate beliefs in the county [14].

Model

We argue that ESG reports are conceptualized within the headquarters of firms and that being exposed to a climate disaster will cause a change in opinion and strategic decisions concerning environmental commitment. Additionally we employ an alternative measure of exposure, presence in the news.

ESG reports are published in a lagged fashion, implying that for instance a large storm in 2021 will affect the ESG report of 2021 (see timeline on top right). We will estimate a very simple model that will be subject to a multitude of concerns and results are in no way assumed to be reliable. We will restrict our sample to the firms that were treated either in 2022, 2023 or not all to not have our results be driven by firms that were treated in the first period and/or in every period. The estimated equation is:

$$ClimateSentiment_{i,c,s,t} = \alpha_i + \beta_s + \gamma_c + \delta * D_{c(i),t} + X_{i,c,t}\mu + t + \epsilon_{i(c),t}$$

Results

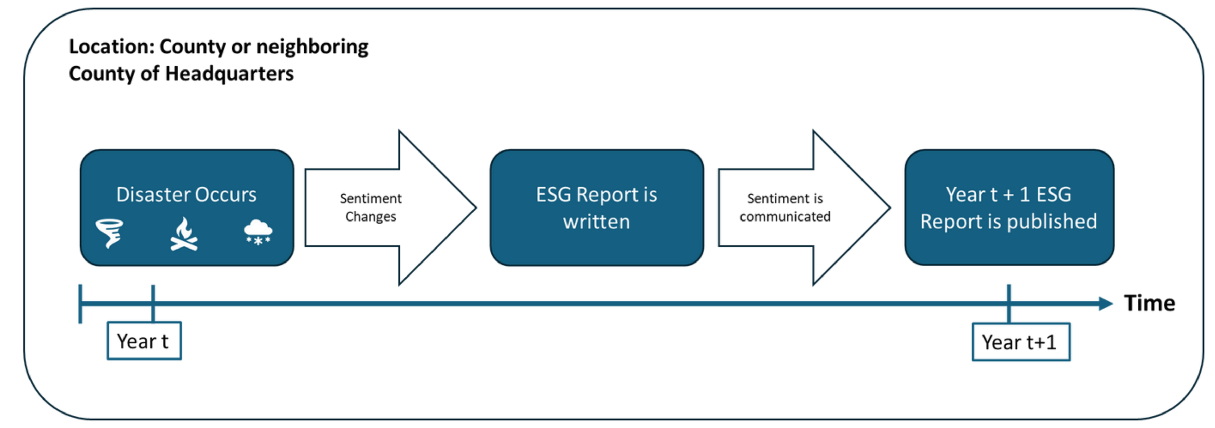
Limited data availability restricts the options for estimation and robustness checks like pre-trends or event studies are not feasible. The endogeneity of firms' locational choice cannot be addressed in sufficient detail. Our estimation is hence subject to critical assumptions and results should be interpreted carefully.

Table 1: Staggered Differences-in-Differences Estimates

	Dep.Var. = ESG Sentiment			
	Naive DiD	Naive DiD	Naive DiD	CS (2021) - DiD
Exp. Climate Disaster	0.460	0.616	0.515	0.675***
(ATET)	(0.37)	(0.59)	(0.59)	(0.24)
	[0.249]	[0.365]	[0.336]	[-]
Obs.	93	93	93	93
R^2	0.792	0.794	0.813	-
F-Stat.	1.532	0.759	1.306	-
Linear Time Trend	No	Yes	Yes	-
Control for Beliefs?	No	No	Yes	-

Note: The table presents the effects of major disaster declarations by the FEMA on ESG sentiment scores. Treatment occurs within the reporting year of the ESG Report. The first three columns show standard staggered DiD estimates and include Firm, County and State Fixed Effects. The last column employs the Callaway and Sant'Anna (2021) estimator. Alternative Specifications and Goodman-Bacon Decomposition found in Appendix. Clustered standard errors (county-level) in round brackets, Conley Standard Errors accounting for serial and spatial (50 Km) correlation in square brackets.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We find (very) limited evidence for a positive effect of disaster exposure on ESG sentiment, implying that firms will increasingly talk about business opportunities related to climate change in the aftermath of a disaster.



Web Scraping Comparison

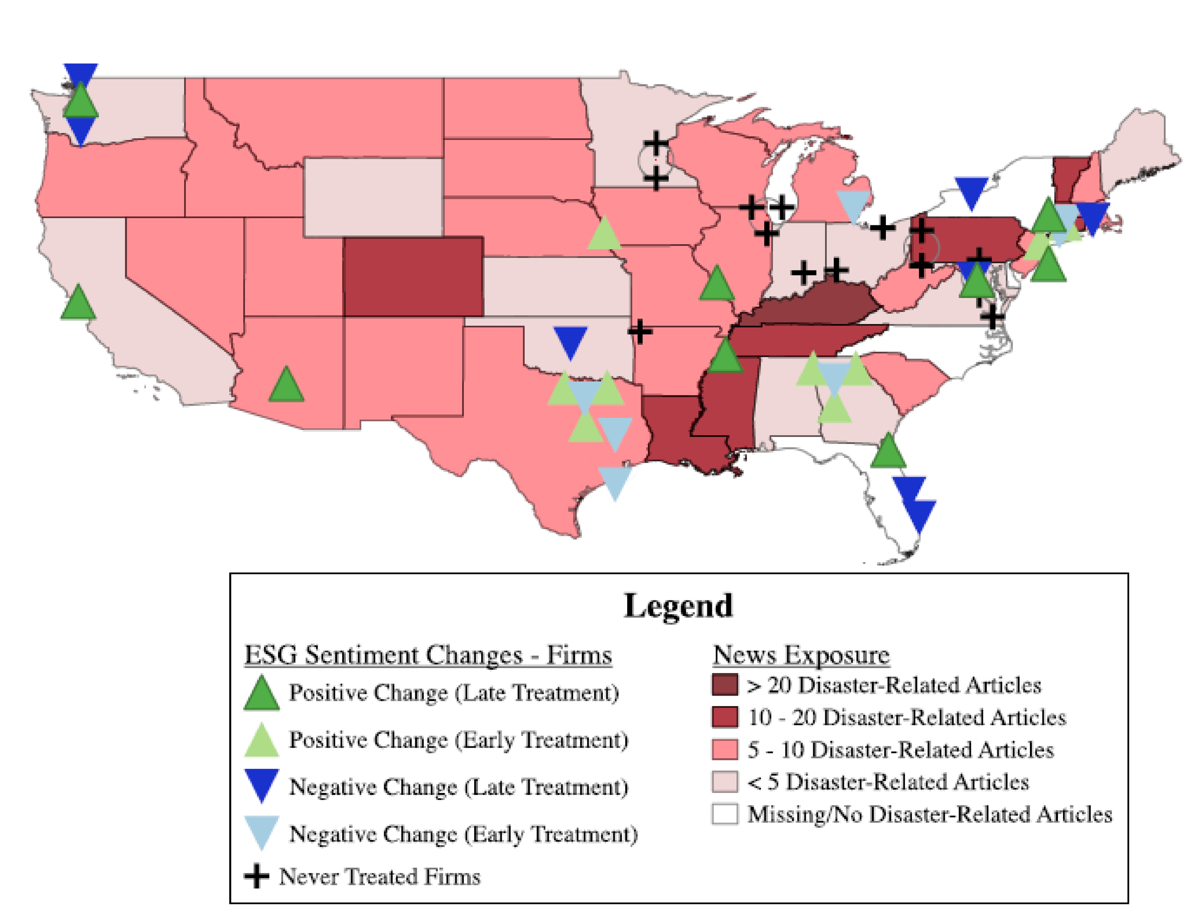
For the Web Scrapping Comparison we follow the below-mentioned steps:

1. **Scraping Data**:
Implemented the scrape_google_news function to fetch articles from Google News RSS feeds using disaster-related keywords and filtered articles based on keywords, publication dates (2020–2023), and source trustworthiness.
2. **Entity Classification**:
Queried news articles for both companies and U.S. states separately and identified and categorized results as either "Company" or "State."
3. **Result Organization**:
Consolidated results into a structured dictionary (all_results) with entities as keys and articles as values.
4. **Output Statistics**:
Counted the number of companies and states with climate-related news; computed the total number of articles found across all entities and analyzed and summarized articles by year.
5. **Data Export**:
Saved results to a JSON file (disaster_news.json) for further analysis; exported results to a CSV file (disaster_news.csv) formatted for use with tools like QGIS, including fields for entity name, type, title, source, trust status, and publication date.

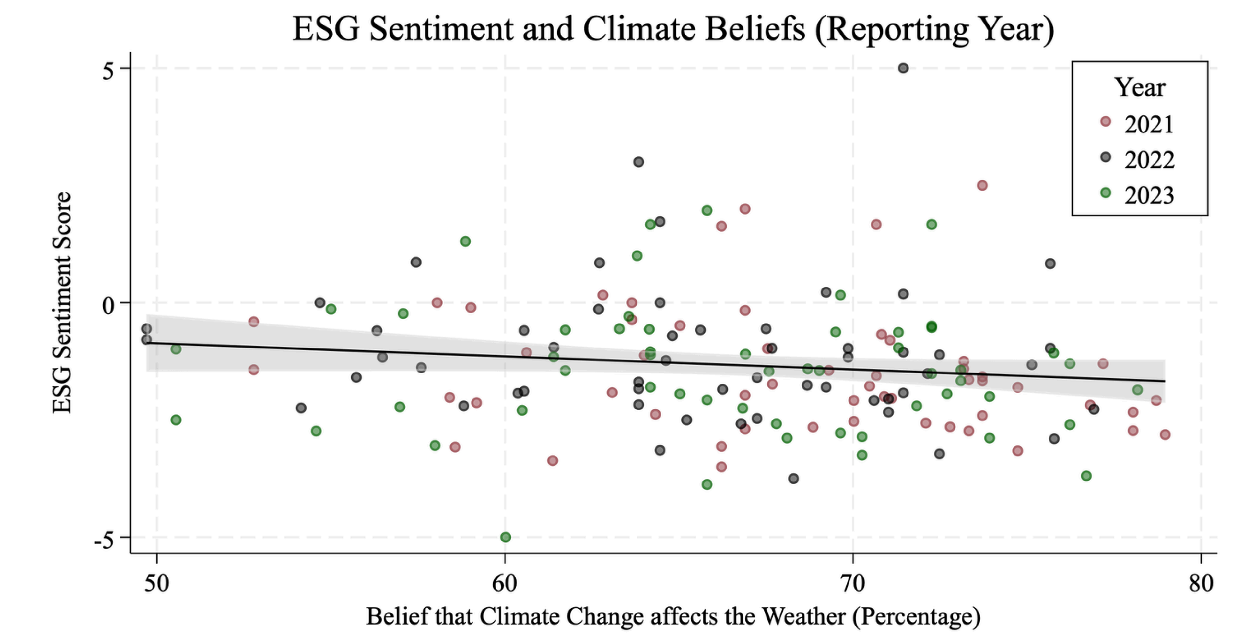
Possible Explanations

This map illustrates climate disaster news exposure and ESG sentiment changes following disasters. While positive sentiment changes dominate, the variability across regions and firms indicates that responses are not uniform. Areas with higher media exposure show more pronounced ESG responses, highlighting the potential role of news in shaping firms' environmental, social, and governance attitudes. Some geographical trends also can be observed like the Midwest and Southeast regions show higher disaster news exposure (dark red) and the West Coast and Northeast generally have lower disaster-related news exposure. Firms are also more likely to be located in lower risk regions illustrating the endogenous locational choice.

Map: ESG Sentiment Changes after Climate Disasters and News Based Climate Disaster Exposure



This graph shows the correlation between climate beliefs (in percentage) and ESG sentiment scores across firm's for the years 2021, 2022, and 2023. It implies that ESG sentiment changes do not seem to be driven by local belief changes but rather by other omitted factors.



Note: This graph presents the stylized relationship between county level climate beliefs and ESG sentiment across Firms' locations. Climate beliefs are surveyed in the reporting year of the ESG report. The diagram additionaly shows a fitted linear function including the 95% confidence band. Data: Climate beliefs from Howe et al. (2015), Sentiment Scores from textual analysis.

Conclusion

In summary, the regressions, maps and graphs suggests that beliefs about climate change affecting weather and the occurrence of environmental catastrophes do not strongly predict ESG sentiment scores across firms. Although climate disasters can lead to changes in ESG sentiment for some companies, the results are not uniform. Media exposure (number of disaster-related articles) might play an important role in amplifying or motivating these changes. Nevertheless, isolated local climate beliefs have little direct influence on ESG scores. Regions with greater exposure to disasters and news exhibit more pronounced ESG responses, mainly positive although the reaction of companies is not uniform. Analyzing other factors, particularly the role of institutional investors [15,16] would be an important extension for further research.

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