Climate Language Model: How CEOs Respond to Climate Change

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Abstract

This paper investigates the implications of the recent surge in large language models (LLMs) and advancements in natural language processing (NLP) for finance research. To quantify firm-level financial risks caused by climate change using earnings conference call transcripts, I employ one of the most advanced NLP techniques and test its validity in the context of executive compensation. I document evidence that physical and transition climate risks, as identified by a modern LLM, are negatively correlated with CEO pay structure and total compensation. This relationship is statistically significant and consistent with recent climate finance literature findings, implying that firms are actively incorporating climate change criteria into their executive pay schemes. In particular, the observed reduction in stock-based compensation in response to physical climate shocks suggests a divergence in how managers and the market perceive the impact of the physical aspects of climate change on firm valuation. In addition, I find the effect of climate risk on CEO stock-based compensation becomes significant after the Paris Climate Agreement.

Keywords and phrases: CEO compensation, climate change, machine learning, natural language processing, corporate governance, text mining, pay-performance sensitivity, stock option.

1 Introduction

2 Measuring Climate Risk with BERT

The Task Force on Climate-Related Financial Disclosures (TCFD) proposed in its 2017 report to categorize financial risks arising from climate change into two types. According to the TCFD and U.S. Environmental Protection Agency (EPA), climate risks are broadly classified into physical climate risks and transition climate risks. Physical risks refer to the direct impacts of climate change, either acute extreme weather events, such as hurricanes and wildfires, or chronic long-term shifts in climate patterns such as rising temperatures. Transition risks relate to the financial risks that arise from the process of transitioning to a low-carbon economy, including policy changes, technological shifts, market reactions, and reputational risks.

The lack of a credible measure that reflects these multifaceted aspects of climate change is a major challenge in climate finance research. I follow the recent literature's approach that exploits textual information in earnings conference call data to measure these risks (Sautner et al., 2023; Li et al., 2024). In this section, I revisit the advantages of using earnings call data and how LLMs can improve existing measures. Then, I explain how I built climate risk exposure measures using DeBERTa.

2.1 Corporate climate risk in textual data

As a relatively new topic in finance, climate risk has only recently begun to receive significant attention. One of the most significant challenges in advancing research in this field is that, there is no consensus on how to measure it (Giglio, Kelly, and Stroebel, 2021; Kolbel et al., 2023; Li et al., 2024). Previous studies have tested various variables as proxies for climate risks, and Giglio, Kelly, and Stroebel (2021) pointed out that it is important to distinguish between several categories of climate risks. Furthermore, Sautner et al. (2023a) noted that the impact of climate change may differ across industries and companies, necessitating disaggregated measures that can reflect these differences.

For example, existing studies have used variables such as temperature, sea level, CO2 emissions, or ESG ratings to quantify climate risks[1]. However, these measures have limitations: they either reflect only one aspect of climate risk, making it difficult to capture its multifaceted nature adequately, or they lack information on firm-level exposure. In the case of ESG ratings, there are issues with selection bias and availability (Li et al., 2024).

These limitations of existing methods have led recent literature to propose quantifying climate risks by dissecting them into categories using textual data (e.g., Faccini, Martin, and Skiadopoulos, 2023; Kolbel et al., 2023). In particular, Sautner et al. (2023a) and Li et al. (2024) identified climate risks from earnings conference call transcripts. There are several advantages to using this data. Earnings call transcripts document quarterly discussions between a company's management team, industry analysts, investors, and media representatives. These conversations cover the company's strategic direction, operating conditions, and financial performance. A key advantage of using the earnings calls is rich, detailed information about the climate risks a firm faces that go beyond what's available in public sources (Li et al., 2024). Due to the two-way communication and information exchange, these are less subject to selection bias compared to sources such as regulatory filings, which are highly scripted. Moreover, they can reflect market participants' assessments about how climate change affects individual firms (Sautner et al., 2023a). The effectiveness of measuring topic-based measures at the firm level from earnings call transcripts has been demonstrated in studies such as Hassan et al. (2019, 2023). Therefore, I follow the recent literature that exploits textual information in earnings conference call transcripts to identify risks to construct my firm-level climate risk measures.

Sautner et al. (2023a) and Li et al. (2024) assume that the frequency of specific topics mentioned in earnings calls serves as a proxy for the degree to which a company is exposed to risks related to those topics. Based on this, they defined a company's climate risk

[1]See, for example, Bolton and Kacperczyk (2021), Cohen et al. (2023), Hong, Li, and Xu (2019), and Goldsmith-Pinkham et al. (2023)

exposure as the share of earnings call conversations in a transcript devoted to physical and transition climate risk to measure climate risks by category. They measured this by scaling the number of climate change-related keywords (or bigrams) mentioned in the document by the total number of words (or bigrams) in the document. Such dictionary-based approaches have issues with accuracy and efficiency as they rely on a pre-defined set of keywords. To address these problems and measure risk exposure with higher accuracy, I employed a natural language processing technique using a contextual neural network, similar to Kolbel et al. (2023). I build an algorithm that identifies information about climate risk contained in sentences, classifies the sentences, and calculates exposure by computing the proportion of relevant sentences in the entire transcript.

2.2 Bidirectional Encoder Representations from Transformers (BERT)

Since earnings call transcripts are textual data, an NLP approach is required to process and create quantitative measures. To this end, I use one of the most advanced NLP techniques, DeBERTa-v3, which is based on the popular language model Bidirectional Encoder Representations from Transformers (BERT). For simplicity, I will refer to the language model used in this study, DeBERTa-v3, as BERT hereafter. Fundamentally, my algorithm works similarly to the approach of empirical finance literature that uses textual data for sentiment analysis (for example, Jiang et al., 2019). Instead of sentiment, I use BERT to identify whether sentences in earnings conference calls contain information about climate change. I scale the number of relevant sentences by the total number of sentences and use it as a proxy for the degree to which each company is exposed to climate risks.

BERT is a deep neural network developed by researchers at Google (Devlin et al., 2019) based on Transformer architecture (Vaswani et al., 2017). NLP through such contextual neural networks has many advantages compared to traditional text mining techniques. To name a few, firstly, the cost of training the model is low. BERT has already been trained on a vast amount of natural language data, so it can be fine-tuned to handle desired tasks with relatively few training samples. In other words, it already includes information about the structure of natural language and words, so researchers only need to instruct the model on the nature of the task it needs to perform. My study sample includes a total of 236,547 earnings call transcripts from 2006 to 2022, but only 170 sample transcripts are used for fine-tuning.

Secondly, BERT is a large language model pre-trained on a large corpus of documents so that its contextual representations capture general natural language patterns. Specifically, BERT is designed to generate contextual word embeddings, meaning that the representation of a word is influenced by its surrounding context, which includes word dependencies and sentence structures. Therefore, BERT can understand context, allowing it to identify similar meanings even when presented with keywords not in the researcher-specified dictionary or information not in the training set, by analyzing the sentence's context. Based on these advantages, BERT shows superior performance in sentence classification tasks compared to existing machine learning methods such as bag of words, tf-idf, and n-gram search. In particular, Kolbel et al. (2023) demonstrated BERT's excellent ability to classify climate change-related sentences even in regulatory disclosures like 10-K filings (which use more refined language compared to transcripts). Furthermore, the natural language understanding capabilities and versatility of Transformer-based large language models (for example, Brown (2020), also known as ChatGPT) like BERT, have already been proven through the experiences of a wide range of users.

In this study, I utilitzed DeBERTa-v3 (He, Gao, and Chen, 2023), a variant of BERT developed by Microsoft, to further enhance classification performance. DeBERTa was first proposed by He, Gao, and Chen (2020) to improve the original BERT's issues and performance, and DeBERTa-v3 is the latest and best-performing version to date. According to the SuperGLUE benchmark (Wang et al., 2019), which evaluates the performance of language understanding models, DeBERTa-v3 is the only variant of BERT that surpasses the human baseline as of August 2024, achieving an average score of 90.3 compared to 89.8 for non-expert human performance. It also significantly outperforms the original BERT (69.0) and GPT-3 (Brown, 2020) (71.8). Furthermore, at the time of writing, DeBERTa is the only publicly available language model with a known structure (Transformer-BERT) that shows better natural language understanding capabilities than human baselines, making it an excellent choice for research applications.

BERT itself only generates contextual embeddings (in other words, it converts natural language into numerical code for processing) and does not perform classification tasks. These processed sentences can be combined with a separate classification head (another neural network) to form an algorithm that performs classification tasks. My algorithm builds on BERT (DeBERTa-v3-large) with a single fully connected linear layer of size 1,024. This linear layer acts as a neural network classifier, receiving the output from BERT and calculating the probability of a given sentence belonging to each class. This process can be briefly expressed by the below formula. Let s be a natural language sentence, $\ell = 1, \ldots, n$ represents the class of the sentence, and $\mathbb{C}^\ell$ is the space to which sentences of class ℓ belong, the probability that the label of s is ℓ is as follows:

$$P(s \in \mathbb{C}^\ell) = \sigma(BERT(s)), \text{ for } \ell = 1, \ldots, n, \tag{1}$$

where BERT is a function that processes natural language, and σ corresponds to the neural network model for classification. If there are n classes in total, this algorithm calculates n probabilities for one sentence. For more detailed explanations about BERT, refer to the appendix.

I ultimately classify sentences into 4 classes: sentences unrelated to climate change or environmental issues (labeled *General*), sentences mentioning environmental issues but not related to climate change (labeled *Other*), sentences related to transition risk among climate change-related risks (labeled *Transition*), and sentences dealing with physical risk (labeled *Physical*). Climate change is one of several environmental issues caused by human activities. Because of this, sentences that discuss environmental problems not directly or only indirectly related to climate change may introduce confusion in the classification task. Therefore, to maximize classification performance, I employed a three-stage evaluation process, rather than assigning a sentence to a class in a single step. The BERT classification models used at each stage were trained with distinct objectives to enhance the accuracy of classification.

First, in the initial stage, a binary classification BERT is used to identify and select sentences that mention content related to the natural environment (*General* or *Environmental*). In the second stage, a multiclass classification BERT reclassifies the environmental sentences selected in the previous stage, determining whether they are related to climate change or are environmental but not directly climate change-related (recycling, pollution, etc.). Most sentences complete their classification with this two-stage classification (*Transition*, *Physical*, and *Other*), and the number of sentences for each label in the document is counted. Finally, to account for the possibility of a sentence belonging to multiple classes (i.e., *Both*, mentioning both transition risk and physical risk in one sentence), another binary classification BERT is applied. The results are then added to the counts from the previous stage. This method results in more accurate classifications and reduces errors compared to assigning a sentence to a class in a single step.

The training set consists of 170 transcripts. It was built by selecting one transcript per sector each year (10 sectors$\times$17-year sample period) from the earnings call transcripts of U.S. public firms between 2006 and 2022, based on the GICS sector code. All transcripts were examined to measure relevance using climate bigrams by Sautner et al. (2023a), and one of the top 10 scoring transcripts for each sector each year was randomly selected. I merged short sentences to eliminate meaningless sentences (for example, " Good morning and thank you for joining us.") and to provide context better. Specifically, I measured the length of each sentence in the earnings call transcripts by the number of tokens, and sentences are merged until the resulting sentence did not exceed 128 tokens. Comments from the operator are removed. After this process, the training set contains 5,390 (reduced from 33,091 before merging), and the final sample includes 18,749,763 (down from 70,757,543 before merging).

When measuring climate risks from earnings call transcripts, the choice of hyperparameters was found to have little impact on model performance. However, BERT was relatively sensitive to overfitting (e.g., as epochs increased, certain classes reduced false positives while increasing false negatives, and the opposite phenomenon occurred in other classes) when there were more than 2 classes to classify. To prevent overfitting, early stopping is applied. Additional model details are relegated to the appendix. The specific process of constructing measures is discussed in the next subsection.

2.3 Construction of climate risk exposure measure

The algorithm used in this paper is essentially a neural network classification model for natural language data. I refer to the entire algorithm as BERT for simplicity. For illustration purposes, I define $\mathbb{C}$ as a conceptual space for natural language sentences. Within this space, $\mathbb{C}^\ell$ is a subset (or a region) of $\mathbb{C}$ for $\ell \in \{Gen, Env\}$. Each $\mathbb{C}^{Gen}$ and $\mathbb{C}^{Env}$ represents a partition for general and environmental sentences, respectively. In other words, all natural language sentences (elements in $\mathbb{C}$) can be categorized as either general or environmental. I use the labels *Env* and *Environmental*, and *Gen* and *General* interchangeably.

In the first stage, I implement a binary BERT model trained to determine whether a sentence contains information related to environmental topics. Let $s_j^{i,t}$ be a sentence in an earnings call transcript of firm i at period t. For each $s_j^{i,t}$, I assign a class as

$$L_j^{i,t} = \begin{cases} Environmental & \text{if } P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6, \\ General & \text{otherwise,} \end{cases} \tag{2}$$

where $P_1(s_j^{i,t} \in \mathbb{C}^{Env})$ is the probability calculated by the first BERT that the sentence belongs to the *Environmental* class, i.e., the sentence mentions the natural environment. L_j stands for the class label of the j'th sentence in the document. BERT calculates the probabilities for both classes, and $P_1(s_j^{i,t} \in \mathbb{C}^{Env}) + P_1(s_j^{i,t} \in \mathbb{C}^{Gen}) = 1$. I set the threshold for being a relevant sentence to be higher than 50%, to enhance accuracy[2].

Given that the sentence $s_j^{i,t}$ is labeled as an environmental sentence in the first stage, I pass it to the second classifier. This second-stage model is an ensemble of three-class BERT classifiers and determines whether $s_j^{i,t}$ is related to transition climate risks, physical climate risks, or other environmental issues ($\mathbb{C}^{Tran}$, $\mathbb{C}^{Phy}$, and $\mathbb{C}^{Other}$), respectively. These are subsets of $\mathbb{C}^{Env}$. The *Other* class is the reason why I need a two-stage approach and is dedicated to sentences that contain information about the natural environment but are less relevant to climate change (referred to as *other* environmental issues hereafter). Here I allocate a separate class for other environmental issues to ensure optimal classification performance. Otherwise, due to the complexity of climate change, BERT cannot properly distinguish environmental topics irrelevant to climate change.

For example, when a manager mentions their "sustainability effort" or "sustainability practice" during the conference call, the classification of this sentence can vary depending on the context. It can be related to climate change, but it is a broad concept encompassing the entire scope of ESG. Therefore, there may not be enough information to determine exactly what type of climate risk is being referred to. It could be about reducing carbon emissions (transition risk), efforts to prevent water shortages or flood damage (physical risk), or perhaps investment in biodiversity conservation (other risk). Since my goal is to detect climate risks as accurately as possible, statements without additional context should be excluded from the climate risk measure. However, if I simply classified it as *General* in the first stage, since it includes the common keyword "sustainability" that is shared with climate risks, it may cause confusion in the model and there would have been a number of errors, falsely included or omitted in the second stage. To prevent this, I included all sentences that contain information related to any kind of environmental issues in the *Environmental* class.

[2] "Accuracy" does not mean the metric accuracy score.

Although the two-stage approach can prevent omitted samples, classification confusion still remains within the second stage. That is, the model still confuse between climate risks and other risks. In addition, the classification is subtle in this stage compared to the first stage since a sentence may contain information related to both transition and physical risks (or other general environmental information). In sum, the decision surface might be vague for this classification task. To address this problem, I created a hierarchy in the classes and trained BERT to establish priorities between them[3]. If a sentence contains content about both climate change and other environmental issues, I prioritized climate change so that the sentence would be classified as climate change. Additionally, if a sentence addresses both the physical and transition aspects of climate change, I trained it to prioritize the physical aspect. For example, if a sentence contains information related to all three, BERT will classify it as *Physical*. This approach can significantly increase the classification performance, especially when there are many similarities between classes, making classification ambiguous.

Before determining the exact environmental quality of $s_j^{i,t}$, I check whether the classes have similar probabilties (e.g., 33.3%–33.3%–33.3%). If the classification task results in all three labels having similar probabilities, it's essentially no different from randomly picking one of the three. This kind of result occurs when the model is forced to make a classification without any prior information about the task (i.e., without training step). If such results appear even after the model has been sufficiently trained, it means the model has determined that the given sentence doesn't belong to any of the three categories. I call this situation an *abstention*. When abstention occurs, I consider the sentence as misclassified. Misclassified sentences are relabeled as *General* and excluded from the second stage classification. Therefore, the second stage not only works as a distinct classification layer, with

[3] One may instead train multiple binary classifiers for each class and measure scores for all classes of each sentence as Kolbel et al. (2023). This is simpler and can be effective when a sentence covers both transition and physical risks. However, the classification performance of this approach can be relatively low because 1) a sentence can be both *General* and *Climate Change*, which is impossible, and 2) it does not account for the problem of ambiguous sentences explained above.

the advantages mentioned above, but also a safety net that prevents errors (false positives) would have occurred in the first stage.

To maximize the utilization of training samples and reduce potential errors arising from a single model's mistake, I implemented an ensemble using five models. For training the ensemble, I partition the data into five validation sets, with each model trained on one validation set, using the remaining four sets as the training set. The ensemble result is derived from the average of class-wise probabilities, with the abstention threshold set at 40%. In cases where the ensemble abstains, i.e., $\max P_2(s_j^{i,t}) \leq 0.4$ where $P_2(\cdot)$ represents the ensemble probability, the sentence is considered misclassified and excluded from the second stage. Consequently, the overall environmental score (exposure) can be calculated as

$$\begin{aligned} ER_{i,t} &= \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1(L_j^{i,t} = Env) \Big] \\ &= \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6) \times 1(\max P_2(s_j^{i,t}) > 0.4) \Big]. \end{aligned} \tag{3}$$

where $J_{i,t}$ is the length of the earnings call transcript. My sample comprises 18,749,763 combined sentences, of which 597,561 sentences directly and indirectly mention environmental issues.

The environmental sentences used in (2) are then reclassified according to their relevance to climate change based on the second stage probabilities:

$$\begin{aligned} &L_j^{i,t} = \ell \\ &\text{if } P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6 \text{ and } \arg\max_h P_2(s_j^{i,t} \in \mathbb{C}^h) = \ell, \\ &\text{s.t. } \max P_2(s_j^{i,t}) > 0.4, \end{aligned} \tag{4}$$

for $\ell \in \{Tran, Phy, Other\}$, the labels for transition risks, physical risks, and other environmental risks, respectively. I use *Tran* and *Transition*, and *Phy* and *Physical* interchangeably.

Since I prioritize *Physical* over *Transition* in the second stage, it is necessary to check whether *Physical* sentences also contain information relevant to *Transition*. To this end, I apply a third BERT model which is as a binary classifier that determines whether a sentence belongs to $\mathbb{C}^{Tran}$. In the third stage, BERT investigates only *Physical* sentences and ensures the sentences relevant to both types of risks are also included in counts of *Transition* sentences. I do not repeat this process for the *Other* class as the primary purpose of this classification is to identify the attention to firms' climate change exposures. As a result, the criterion for *Transition* is updated as

$$\begin{aligned} L_j^{i,t} &= Transition \qquad (5)\\ &\text{if } \arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Tran,\\ &\text{or } \arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Phy \text{ and } P_3(s_j^{i,t} \in \mathbb{C}^{Tran}) > 0.9,\\ &\text{s.t. } P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6 \text{ and } \max P_2(s_j^{i,t}) > 0.4. \end{aligned}$$

Due to the second condition, *Transition* and *Physical* may not be mutually exclusive[4]. For the third BERT, I require the threshold for a sentence being associated with transition risk (in fact, related to both) to be at least 90%, which is much higher than the threshold of the first-stage BERT. This is because the complexity of the classification task in the third stage (transition climate risk or not) is greater than in the first stage (environment or not). Out of 597,561 environmental sentences, 430,663 sentences are relevant to climate change,

[4]Otherwise, it is possible to create a separate class by re-labeling *Physical* as

$$L_j^{i,t} = Both,$$

if $P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6$ and $\max P_2(s_j^{i,t}) > 0.4$ and $\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Physical$ and $P_3(s_j^{i,t} \in \mathbb{C}^{Tran}) > 0.9$ are satisfied. Then the measures are given by

$$CE_{i,t}^h = \frac{1}{J_{i,t}} \sum_{i=1}^{J_{i,t}} \left[1(L_j^{i,t} = \ell) + 1(L_j^{i,t} = Both) \right] \text{ for } \ell \in \{Tran, Phy\}.$$

and 8,053 sentences turn out to mention both transition and physical risks.

The climate risk exposure measures are calculated as follows:[5]

$$CE^{\ell}_{i,t} = \frac{1}{J_{i,t}} \sum_{i=1}^{J_{i,t}} \Big[1(L^{i,t}_{j} = \ell) \Big], \tag{6}$$

for $\ell \in \{Tran, Phy\}$, and the other environmental risk measure is

$$OER_{i,t} = \frac{1}{J_{i,t}} \sum_{i=1}^{J_{i,t}} \Big[1(L^{i,t}_{j} = Other) \Big]. \tag{7}$$

Note that $ER_{i,t} = CE_{i,t} + OER_{i,t}$, where $CE_{i,t}$ represents the total climate risk before distinguishing between transition and physical risks. However, $CE_{i,t} = CE^{Tran}_{i,t} + CE^{Phy}_{i,t}$ may not hold, due to the presence of sentences that belong to both *Transition* and *Physical*. In addition, the variable OER may not accurately reflect firms' exposure to general environmental risks other than climate risks, as CE^{Tran} and CE^{Phy} may have partially captured its influence.

Table 1 reports descriptive statistics for the transcript-based climate risk exposure measures. I also report fiscal-year-level averages of the quarterly measures, since executive compensation data are available at the annual level. The final sample comprises 39,944 firm-year observations calculated from 145,397 firm-quarter samples. Table A.3 reports averages of the measures by industry sector (six-digit level GICS industry code; comparable to the two-digit SIC code level) and their ranking of these averages. Similarly to the measures of Sautner et al. (2023a), there exists significant variation within industries, indicating that firms experience different levels of exposure to climate change.

Figure 1 Panel (a) shows the quarterly number of calendar year-quarter transcripts from 2006 to 2022 used in this study (colored in blue) and the number of transcripts containing at least one sentence related to environmental risk (colored in green). As previously described, I initially employ a two-stage BERT to identify environmental sentences in the transcripts.

[5]See appendix for detailed formulas.

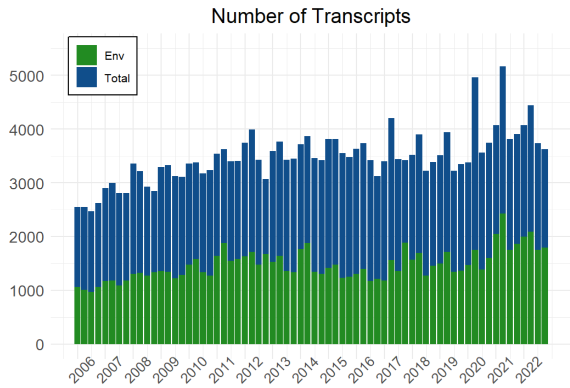
Table 1

Panel (a): Firm-quarter (calendar year) statistics						
	N	Mean	SD	25%	Median	75%
ER	145,397	3.320	6.838	0.000	0.329	3.261
OER	145,397	0.845	2.390	0.000	0.000	0.671
CR^{Tran}	145,397	1.503	5.065	0.000	0.000	0.000
CR^{Phy}	145,397	1.023	2.788	0.000	0.000	0.625
Panel (b): Firm-year (fiscal year) statistics						
	N	Mean	SD	25%	Median	75%
ER	39,944	3.306	6.476	0.000	0.735	3.302
OER	39,944	0.855	2.202	0.000	0.074	0.704
CR^{Tran}	39,944	1.527	4.949	0.000	0.000	0.474
CR^{Phy}	39,944	0.972	2.230	0.000	0.000	0.887

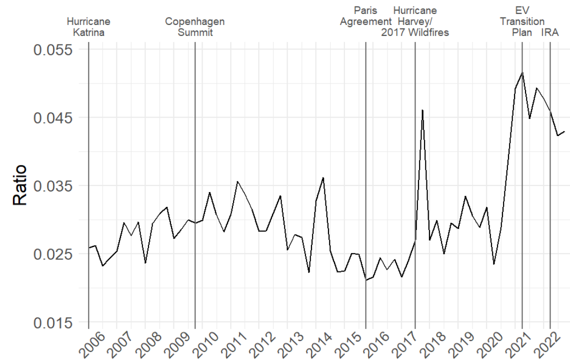
Descriptive Statistics: Climate Risk Measures. This table presents descriptive statistics for climate risk measures at the firm-quarter (calendar year) and firm-year levels. The measures are constructed based on earnings call transcripts of 4,554 distinct publicly traded US firms for the period between 2006 and 2022. When a company conducted multiple conference calls or meetings in the same quarter, the quarterly average was considered as a single firm-quarter observation.

It results in 597,561 sentences (approximately 3.2% of the total sentences) that mention environmental risks. Based on the two-stage classification results, I apply the third BERT to detect sentences that belong to multiple classes. The climate risk measures are then computed as the ratio of sentences in each class to the total number of sentences (merged to 128-token) in the transcripts.

Figure 1 Panel (b) and Figure 2 depict the quarterly trends of the average of the measures ER, OER, CE^{Tran}, and CE^{Phy}, representing the cross-sectional average of the proportion of environment-related sentences among all sentences in the transcripts and their variation. These time series show high quarterly volatility throughout the entire period, with an increasing trend until around 2009-2010 when the Copenhagen Climate Summit took place, then starting to decrease. Mentions of environmental risks began to gradually increase again after 2017, and from 2020, they surged to more than 5% of the entire transcript.



(a) Number of Transcripts in Sample



(b) Quarterly Trends in Ratio of Environment-related Sentences

Figure 1. Number of earnings call transcripts and average proportion of environment-related sentences. Panel (a) shows the number of earnings call transcripts from U.S. listed companies in the non-financial sector that are the subject of this study (colored in blue) and the number of transcripts among those that mention environment-related sentences (colored in green). Panel (b) represents the average occurrence rate of environment-related sentences calculated from the transcripts used in the actual analysis among those in (a).

This seems to be due to the extreme weather events and disasters that intensified from the late 2010s, the resulting increased interest in the environment, and the influence of policies such as electric vehicle transition policies in Europe and the United States, and bills like the Inflation Reduction Act. Except for the high volatility and shocks observed in 2014 and 2017, the trend shows similar tendencies to Sautner et al. (2023a) who analyze climate risks in earnings call transcripts using a bigram search method.

In Figure 2, I plot the topic-based measures of climate and environmental risks over time. Panels (a) and (b) show the proportion of sentences related to transition risk and the weight of transition risk (CE^{Tran}) among environment-related sentences, respectively. Panels (c) and (d) show the quarterly pattern of physical risk CE^{Phy}. When comparing trends of transition and physical risks, transition risk shows relatively low volatility compared to CE^{Phy}, which is greatly influenced by special events such as hurricanes.

As seen in Panel (c), jumps are observed with a slight lag after major US hurricanes, demonstrating that CE^{Phy} effectively captures the physical aspect of climate risk. This strong reaction to physical shocks is similar to the findings of Sautner et al. (2023a) and Li et al. (2024). Notably, a significant shock, likely due to the impact of Hurricane Harvey and California wildfires in 2017, is observed, and high volatility is caused by the influence of irregularly occurring extreme weather events. This confirms that the volatility and two spikes observed in Figure 1 are due to physical risk shocks.

Regarding transition risk, until the sudden increase in interest in electric vehicles and renewable energy in 2020, it appears to be largely unaffected by policy events. For example, it shows a smooth pattern without shocks even during major events like President Trump's withdrawal from the Paris Climate Agreement in 2017. My measure shows a remarkably similar pattern to the transition risk measure of Li et al. (2024). Both measures do not significantly change in response to major international or domestic U.S. events. They both recorded high values in 2008 and 2009, but for about a decade until the late 2010s, they did not exceed their previous peak levels.

Panels (e) and (f) show the trends of other environment-related risks (OER). It shows a similar trend to transition risk. This could be due to the fact that this variable measures a firm's concern around environment issues such as recycling or pollution, which are also subject of politics and societal expectations. However, the actual correlation is weak (0.21). Although OER experiences a jump similar to transition risk in 2020, unlike CE^{Tran}, which maintains consistently high figures, a sharp drop is observed entering 2022. This seems to be due to companies recently starting to focus more on specific global warming issues like carbon footprint rather than taking a general approach to environmental concerns.

3 Literature Review and Hypotheses

3.1 Corporate Environmental Performance and CEO Compensation

Research on CEO compensation is fundamentally based on agency theory, particularly the notion of principal-agent relationships as described by Jensen and Meckling (1976).

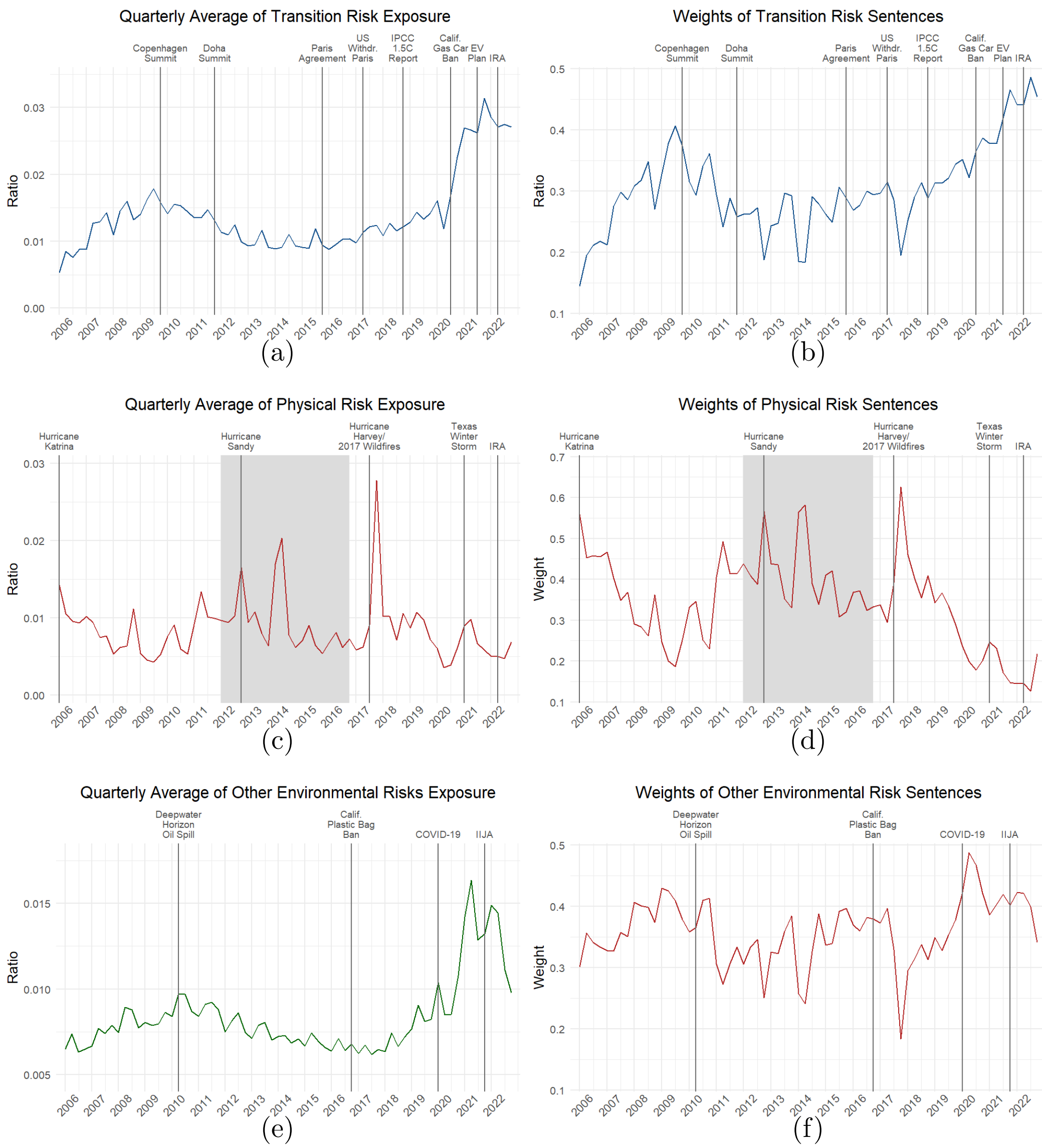


Figure 2. Quarterly trends of climate risks by type. The left columns, Panel (a), (c), and (d), show the average proportion of sentences related to transition risks, physical risks, and other environmental risks mentioned in the earnings call transcripts, respectively. The right columns, Panels (b), (d), and (f), represent the average weight of transition, physical, and other risks among the all environmental sentences mentioned in a transcript. The shaded region in Panels (c) and (d) represents the 2012-2016 Western drought.

According to agency theory, CEOs are rational, self-interested, and opportunistic agents. Thus, compensation should be designed to correlate with the firm's financial performance so that CEOs are encouraged to align their own interests with principals' (shareholders) wealth. Without such a compensation structure, executives may not always act in the best interests of the shareholders, potentially pursuing personal benefits or growth in firm size that enhances their own financial rewards, at the cost of profitability and shareholder wealth. By effectively relating CEO compensation and financial performance, agency costs can be minimized (Coombs and Gilley, 2005).

Building upon agency theory, previous research on the impact of a firm's environmental performance on CEO compensation has adopted stakeholder theory as its theoretical framework. Stakeholder theory extends agency theory by proposing that managers should strive to address the needs of a diverse group of stakeholders, including those of the shareholders–maximizing financial performance. In this view, CEOs can be considered agents not only for shareholders but for all stakeholders, as CEOs have direct control over firm-level decisions that directly affect all stakeholder groups (Hill and Jones, 1992; Coombs and Gilley, 2005). Therefore, CEOs should aim to make decisions and take actions to satisfy all of the firm's stakeholders. The board of directors, in turn, should reward CEOs for maximizing value for these stakeholders, as such actions enhance the overall effectiveness of the firm (Coombs and Gilley, 2005). Among the stakeholders, the natural environment is the primary 'stakeholder' of the firm (Francoeur et al., 2017). Yi et al. (2023) revealed through a meta-analysis of 80 existing studies that a firm's green innovation has a positive impact on financial performance, including profitability. Consequently, from this stakeholder-agency perspective, previous literature suggests that firms aiming to strengthen their environmental commitment should offer their CEOs explicit incentives to implement environmentally-focused strategies (e.g., Stanwick and Stanwick, 2001; Coombs and Gilley, 2005; Cordeiro and Sarkis, 2008; Berrone and Gomez-Mejia, 2009).

Existing research on the relationship between CEO compensation and environmental performance has found mixed evidence. On the one hand, Stanwick and Stanwick (2001) and Coombs and Gilley (2005) reported a negative correlation between environmental reputation/performance and CEO compensation. Employing a stakeholder-enlarged view of agency theory, they interpreted their findings that firms with higher environmental performance gave CEOs incentives to decrease their focus on environmental strategies. Cordeiro and Sarkis (2008) observed that environmental performance affects CEO compensation only in firms with explicit ties between environmental performance and CEO pay. They found that this relationship is marginal and negative.

On the other hand, Berrone and Gomez-Mejia (2009) found that firms with good environmental performance operating in environmentally sensitive sectors reward their CEOs accordingly. They argued that agency theory supports a positive relationship between environmental performance and CEO compensation because a firm's environmental commitment enhances long-term corporate health and legitimacy. The authors also contended since firms face external pressures due to social, cultural, and political beliefs, meeting these societal expectations improves a firm's survival prospects, thus providing an incentive for firms to encourage sustainable practices among their CEOs from an institutional theory perspective.

Francoeur et al. (2017) is a more recent study that found evidence of a negative relationship between firms' environmental commitment and CEO compensation. Instead of adopting the agency theory explanation that this is a punishment for hindered financial performance caused by the increased cost from environmental strategies, they took the perspective of environmental stewardship along with institutional theory. They argued that CEOs may not always act as opportunistic agents, but are willing to act as stewards of the natural environment and accept lower compensation, which explains the negative influence of environmental performance on CEO pay.

However, a firm's environmental performance and its exposure to climate risks may have different impacts. Research specifically focusing on the relationship between CEO compensation and 'climate change' is scarce. Bose et al. (2022) investigated whether the introduction of climate-linked incentive compensation affects a firm's climate change strategy. They found that such incentives are effective in increasing initiatives for the reduction of carbon footprint, but do not improve actual carbon emissions. Winschel (2020) found that cases of linking carbon emissions to CEO performance evaluation and compensation are limited among European firms, and even when such compensation structures are introduced, they are confined to short-term compensation.

Hossain et al. (2023) discovered a positive correlation between climate risks and CEO's equity-based compensation. From the perspective of compensation theory, they interpret this as a result of the CEOs' demand for compensation for more challenging duties and the board's desire for more capable managers due to the increased multi-dimensional business risks caused by climate risks. Their work is similar to my study in that it analyzes the impact on CEO compensation using a firm-level climate risk exposure measure extracted from information in earnings calls. However, their study and mine differ in how climate crisis is measured. Their measure, provided by Sautner et al. (2023a), is based on bigram analysis of earnings calls. I have constructed climate change measures with higher accuracy than the bigram search method by using a more advanced neural network approach. Moreover, to the best of my knowledge, this is the first study to analyze climate change's impact on CEO compensation by separating transition and physical climate risks.

3.2 Climate Finance

As the threats to business and society from climate change have begun to materialize, it has sparked a surge in finance research. In particular, the pricing of climate risks in financial markets is a key issue in the climate finance literature (Giglio, Kelly, and Stroebel, 2021; Stroebel and Wurgler, 2021; Li et al., 2024). In this context, a large body of literature documents evidence that climate risks are priced in stock, derivatives, bond, and real estate markets. Notable studies include Bolton and Kacperczyk (2021, 2023), Engle et al. (2020), Giglio et al. (2021), Goldsmith-Pinkham et al. (2023), Ilhan et al. (2021), and Schlenker and Taylor (2021). However, at the same time, Stroebel and Wurgler (2021) argue that it is still unclear whether asset prices reflect climate risks to the correct degree. They confirm through an extensive survey of academics and practitioners that there is a consensus that asset prices tend to underestimate climate risks.

The question of whether the climate risks affect the equity market is also related to CEO compensation, as a firm's financial performance directly impacts the value of stock-based incentives such as stock options and restricted stock. To avoid potential agency problems, companies design compensation packages to incentivize managers to maximize shareholder value. Stock-based compensation is a primary tool that firms use to better align the risk preferences of CEOs and shareholders (Hall and Liebman, 1998). Stock-based incentives have important effects on CEOs' risk-taking behavior and firm performance (Sanders, 2001; Hou et al., 2020). This compensation structure has seen widespread adoption by corporations starting in the 1990s, and recently, it has come to constitute the major share of CEO pay (Hou et al., 2020; Hossain et al., 2023). Consequently, a firm's stock price serves as an important determinant when the board of directors determines compensation and significantly influences CEO compensation (Hall and Liebman, 1998; Francoeur et al., 2017).

In this regard, I contribute to the growing empirical literature on climate finance by providing a new perspective on assessing the impact of climate risks on firm value. Sautner et al. (2023b), Bolton and Kacperczyk (2021, 2023), Li et al. (2024), and Faccini, Martin, and Skiadopoulos (2023) test how climate risks are priced in the equity market as either a firm characteristic or risk factor. While these studies use different measures to quantify climate risks, they consistently conclude that transition/regulatory risk is priced in the equity market. However, Hong, Li, and Xu (2019), Sautner et al. (2023b), and Faccini, Martin, and Skiadopoulos (2023) draw different conclusions regarding the impact of physical risk. Therefore, in this study, I analyze how the proportion of stock-based compensation in CEOs' total compensation changes in response to climate risks. By doing so, I aim to present new evidence for the pricing of climate risks, focusing on managers' forward-looking view, rather than the market's, regarding the impact of the unprecedented risks on firm value.

This study also contributes to the literature by proposing accurate climate risk measures constructed through applying a sophisticated natural language processing model to earnings call transcripts, which are less scripted and typically timely and informative. A major challenge in climate finance research is the lack of credible measures of climate risk exposure. The most commonly used measures – carbon emissions, temperature, sea level, frequency of natural disasters, and proprietary ESG ratings – all have limitations in either adequately reflecting the multifaceted aspects of climate change or in their coverage. In particular, with such measures, it is difficult to determine how individual firms are affected by climate change (Giglio, Kelly, and Stroebel, 2021). In addition, as pointed out by Sautner et al. (2023a), it is important to develop disaggregated measures that capture variation across firms and reflect market participants' assessments of how climate change impacts each firm. My measures address the limitations of previous papers by providing firm-specific, timely, and multifaceted assessments of firms' exposure to climate risks.

The studies most closely related to my paper are Sautner et al. (2023a) and Li et al. (2024). Both papers propose firm-level measures of climate exposure using earnings call data. Moreover, the measures in Sautner et al. (2023b) and Li et al. (2024) are, like mine, firm-specific and topic-based, and they use these measures to explore the impact of climate risks on firm value as measured by stock returns and Tobin's Q, respectively. However, their studies differ from mine in that they employ bigram search or dictionary-based approaches. Deep neural network models like BERT offer significant advantages in accuracy and efficiency compared to basic text mining methods or traditional machine learning methods such as n-gram models. BERT is pre-trained on vast amounts of natural language data, allowing a single researcher to fine-tune it for sentence analysis with relatively little data. Furthermore, this algorithm can understand context, enabling it to more accurately analyze sentences by judging semantic consistency through the flow of the text and relationships between words, even when they don't match predefined keywords. By employing BERT, I effectively capture sentences that traditional methods might miss (false negatives), thus overcoming a key limitation of previous approaches.

This study is also closely aligned with Kolbel et al. (2023), who used BERT to measure climate exposures. They quantified climate risks of regulatory disclosures based on Form 10-K filings and analyzed their impact on the term structure in the credit default swap market. My research differs from theirs in that it extracts information from earnings calls. During earnings conference calls, company management discusses performance and related factors with analysts and investors. Consequently, these calls contain detailed and bi-directional (i.e., discussions) information about the climate risks a firm faces beyond those that stem from public sources (Li et al., 2024). Compared to regulatory disclosures, which may selectively reveal only the minimum information necessary to avoid legal disputes, conference calls, where investors directly participate in the discussion, can be expected to better reflect the actual risks faced by the company. I use DeBERTa-V3, a recent variant of BERT proposed by He, Gao, and Chen (2023) that significantly improves upon the base BERT's performance. Furthermore, in order to minimize measurement errors, I trained multiple models, combined with an ensemble method, to classify sentences sequentially. This advanced methodological approach, combined with the rich data source of earnings calls, enables my study to provide more comprehensive and nuanced measures of firm-level climate risk exposure.

3.3 Hypothesis Development

In this subsection, I will present the hypotheses of this study while elaborating on its connection to research on CEO compensation and studies on the impact of climate change on firm value and market risk. First, the proportion of stocks and stock options in CEO compensation has been showing an increasing trend and now accounts for the majority of compensation (Hossain et al., 2023). Consequently, climate change affects CEO compensation through a more direct channel, beyond indirect channels such as the role of the natural environment as a stakeholder or its impact on corporate costs and profitability.

Secondly, the relationship between climate change and executive stock-based compensation provides insights into how firm insiders assess the impact of climate risks on firm value. This is because analysis of the relationship between climate risk exposure and stock-based awards, particularly how its proportion in total compensation changes in response to the risk exposure, will provide evidence about management's outlook on market risk and stock value. This perspective also differentiates this study from existing research in climate finance and CEO environmental performance pay.

Specifically, if the proportion of stock-based compensation in CEO's total compensation changes significantly along with the firm's climate risk exposure (as measured by climate change-related mentions in earnings call conferences), this can be interpreted in two ways. First, considering that the long-term effect of climate change on the firm's profitability is uncertain yet, it can serve as evidence that they are genuinely committed to environmental dedication, reflecting this commitment in executive compensation rather than merely engaging in "greenwashing". Second, it can be interpreted as reflecting the management and board's view that climate change is a factor that will significantly impact stock prices. Executives, compared to external investors, have more detailed information about the firm's operations, future prospects, and risks (Jensen and Meckling, 1976), potentially placing them in a superior position regarding stock price forecasts (Jaffe, 1974). Moreover, given that CEOs exert significant influence in setting their own pay (Hossain et al., 2023), they have an incentive to adjust their compensation structure if they believe stock prices will change significantly in the future.

In sum, if executives believe, based on insider information, that climate change will act as a risk (or opportunity) that potentially affect firm value and financial performance significantly, they will respond by decreasing (or increasing) the proportion of stock-based compensation and increasing (or decreasing) the proportion of fixed salaries. Therefore, I formulate hypotheses on the relationship between climate change and CEO compensation by approaching the impact of climate risks on the firm's market performance and the subsequent predictions of insiders (executives and directors).

Among the two aspects of climate risks, previous literature draws relatively consistent conclusions about the impact of transition risk. Kolbel et al. (2023) found that transition risk brings a strong risk-perception effect (after the Paris Agreement), significantly increasing the credit swap spread for firms in environmentally susceptible industries. Faccini, Matin, and Skiadopoulos (2023) demonstrate that a long-short portfolio, sorted by stocks' betas to a textual climate policy risk factor, yields a positive alpha. They argue that the positive alpha suggests that regulatory risks are associated with a positive risk premium. Furthermore, Sautner et al. (2023b) showed that exposure to transition risk has a positive impact on a firm's future expected return, delivering a positive risk premium. Li et al. (2024) found that increased exposure to transition risks leads to a decrease in firm value as measured by Tobin's Q. In short, there is a consensus that increased transition risks command a positive risk premium and are associated with higher market risk. This is also consistent with existing research using other proxies for transition risk, such as carbon emissions (e.g., Bolton and Kacperczyk). Thus, provided that CEOs are risk-averse (Eisenhardt, 1989; Jensen and Murphy, 1999), they will have the motivation to reduce stock-based incentives in situations of increased price volatility. Moreover, transition climate risks are driven by institutional changes within an economic system. These institutional pressures demand proactive responses from CEOs (Berrone and Gomez-Mejia, 2009; Francoeur et al., 2017), and if they clearly harm firm financial performance, an increase in such risks will affect the CEO's total compensation negatively. Therefore, I postulate my first hypothesis as follows:

Hypothesis 1a. CEOs of firms with higher exposure to transition climate risks reduce the proportion of incentive-based compensation in their total rewards in subsequent years.

Hypothesis 1b.CEOs of firms with higher exposure to transition climate risks will receive lower total compensation in subsequent years.

In contrast, existing climate finance literature presents complex and somewhat weaker results regarding the impact of physical climate risks. Therefore, the question of how physical risk affects CEO compensation structure (stock-based incentives) becomes more intriguing. First, according to the survey by Stroebel and Wurgler (2021), while the importance of physical risk will increase over the next 30 years, it currently appears less significant in terms of its impact on asset prices compared to transition risk. Hong, Li, and Xu (2019) are one of the studies testing how stock markets price physical risks. They showed that food stock prices do not sufficiently reflect physical risks represented by drought trends. More comprehensive tests using Faccini, Martin, and Skiadopoulos's (2023) natural disaster news index or Sautner et al.'s (2023b) earnings call measure also failed to find evidence of a risk premium associated with physical shocks.

On the other hand, it appears that derivative markets reflect physical risks more actively. For instance, Shlenker and Taylor (2021) find that weather derivative prices are generally in line with temperature trends over the past two decades. In particular, Kruttli, Tran, and Watugala (2023) found that extreme weather events increase the implied volatility in the stock options market. They observed that the market's response became more accurate and efficient following Hurricane Sandy.

Contrary to the implications of Kruttli, Tran, and Watugala (2023), Kolbel et al. (2023) reported that physical risks have the effect of reducing CDS spreads, albeit with marginal statistical significance. They interpret this as physical risks leading to a decrease in risk premia, attributing it to the uncertainty reduction effect. However, they note that the premise of this effect is that "Market participants have no access to managers' private information and must estimate today's asset value based on publicly available information like accounting figures or regulatory disclosures" (p. 36). In the context of this study, such an effect cannot be expected since the dependent variable represents the managers' view.

Rather, due to the nature of physical shocks, they are driven by the laws of physics rather than politics, and they materialize in extreme weather events and their knock-on effects (Kolbel et al., 2023). These are not new risks; but they are well known and become more frequent and extreme as climate change progresses (Permesan, Morecroft, and Trisurat, 2022). Even if management possesses private information, it is unlikely to provide better predictive power for the intensity and forecast of extreme weather events compared to the best public information available. At the same time, physical risks are hardly insurable or diversifiable due to their geographical correlation (Charpentier, 2007). Consequently, only the risk-perception effect will be reflected in managers' outlook, and executives will be reluctant to receive compensation with unstable value in situations where an increase in unpredictable and unhedgeable risks is anticipated.

While extreme weather events can directly impact a company's operations, it's difficult to blame management for damage caused by natural disasters. Furthermore, in terms of direct performance of a firm, Addoum, Ng, and Ortiz-Bobea (2020) found evidence that temperature shocks are unrelated to a firm's sales, productivity, and profitability, even though not all types of physical shocks are considered. Thus, boards will not penalize CEOs for such risks. The result will be instead an adjustment in the proportion of stock-based incentives and fixed compensation. Therefore, I expect that:

Hypothesis 2a. CEOs of firms with higher exposure to physical risks reduce the proportion of incentive-based compensation in their total rewards in subsequent years.

Hypothesis 2b. Physical risks will have no impact on the total amount of CEO compensation.

The pricing effect of climate risks and their impact on corporate financial performance have likely become significant in recent years as social awareness of climate change has increased (Giglio, Kelley, Stroebel, 2021; Li et al., 2024). Heightened public attention to global warming increases the probability of pro-climate policy adoption (Ilhan, Sautner, and Vilkov, 2021). Certain events contribute to shaping public perceptions of climate change and focusing attention on this issue (Li et al., 2024). Several studies have demonstrated that climate change became price and risk-relevant following key events such as the 2009 UN Climate Change Conference in Copenhagen, the SEC's 2010 release of guidelines on disclosure requirements related to climate change issues, the 2015 Paris Climate Agreement, and the election of Donald Trump in 2016 (Ilhan, Sautner, and Vilkov, 2021; Kolbel et al., 2023; and Li et al., 2024).

These events likely function as regulatory shocks that draw attention to transition risk. Indeed, Kolbel et al. (2024) tested two aspects of climate risk before and after the Paris Climate Agreement and demonstrated that only transition risk showed economically significant effects following the agreement. Similarly, Li et al. (2024) found that transition risk only began to impact firms' market valuations after the SEC's guidelines were issued in 2010. In both cases, transition risks produced a risk-perception effect, resulting in decreased firm valuation and increased risk in the derivative market.

Consequently, we expect the effect of climate risk on CEO compensation to be more significant in recent years than in the past, likely strengthening after certain key events. This trend is expected to be particularly pronounced for transition risks, as regulations and social expectations formed due to regulatory shocks would have begun to significantly impact stock prices and corporate performance. However, the temporal difference for physical risks is less clear. Physical risks have predominantly manifested as acute events like natural disasters rather than chronic risks until recently, and as Kolbel et al. (2023) noted, extreme weather events are not a new risk factor. Moreover, political events do not directly increase the occurrence of natural disasters.

As a result, considering my previous hypotheses, the expectation is that the negative correlation between transition risks and CEO compensation would have become statistically significant only after a regulatory shock. Conversely, the impact of physical risks on stock-based compensation and total pay is expected to remain unchanged over time. To test this, I hypothesize that the influence of climate risk on CEO compensation changed after the Paris Climate Agreement, which is an event that altered the perception of climate risk for both investors and corporations through transnational consensus. Therefore:

Hypothesis 3a. The impact of transition risks on CEO compensation will become statistically significant after the Paris Climate Agreement.

Hypothesis 3b. The impact of physical risks will not change due to the Paris Climate Agreement. In other words, its significance (or lack thereof) will remain the same before and after the agreement.

4 Data

4.1 Earnings call transcripts

I construct firm-specific, time-varying measures of the focus on climate risk exposure using transcripts from quarterly earnings calls of publicly listed US firms. The transcripts are collected from the Refinitiv StreetEvents database.

The measures were constructed using all types of earnings calls that include both the management presentation and the Q&A session with analysts. Specifically, the sample includes transcripts from earnings, corporate, guidance, sales, and analyst conference calls, as well as analyst and shareholder meetings from 2006 to 2022. I used only transcripts from publicly listed companies in the United States (corresponding to CRSP exchange codes 1, 2, and 3), excluding companies in the financial sector based on GICS (sector code 40). The exchange codes required for identification were obtained from CRSP, and the GICS classifications were confirmed from Compustat. The sample satisfying these criteria during the study period consists of 236,547 conference call transcripts from a total of 4,554 companies. The total number of sentences in this sample is 70,757,543 (18,749,763 merged 128-token sentences).

4.2 CEO compensation and firm fundamentals

To test the hypothesis on the impact of climate change risks on CEO compensation structures, I use the CEO total compensation (*Total pay*) and the proportion of stock-based incentives (*Pay ratio*) as the dependent variables. Stock-based, or equity-based compensation includes the total value of restricted stocks granted and the total value of stock options granted. Restricted stock is based on the dollar value on the grant date, and options are valued using the Black-Scholes option pricing formula. Consistent with previous research on executive compensation (Jensen and Murphy, 1990; Frydman and Jenter 2010; Berrone and Gomez-Mejia 2009; Cordeiro and Sarkis, 2008), total compensation is measured as the sum of salary, annual bonus, long-term incentive plan, other cash payouts, and the stock-based incentives. I took the natural logarithm of these variables to correct for skewness in the distribution. To analyze both the short-term and long-term impacts of climate change issues on compensation, I use two timeframes in the study. We examine the relationship between the climate risk measures and compensation data for the following fiscal year (t+1) to capture recent effects. Additionally, I check the average compensation over the subsequent three fiscal years (t+1 to t+3) to assess the longer-term influence of climate change risks on executive pay. I collect data on CEO compensation from the Compustat ExecuComp database.

Control variables are selected based on previous research on the relationship between corporate environmental performance and CEO compensation, as well as studies on pay-for-performance, given that incentive-based compensation is a key dependent variable. The first set of control variables pertains to firm financial performance, which is widely recognized as an important determinant of CEO compensation (Hall and Liebman, 1998; Berrone and

Gomez-Mejia, 2009; Francoeur et al, 2017). I measure financial performance using *ROA*, return on assets, and *Return*, a firm's annual stock return, following prior studies (Cordeiro and Sarkis, 2008; Hou et al., 2020; Claude et al, 2017; Cohen et al., 2023). The standard deviation of monthly stock returns over the year is also included as *Volatility*. (Cohen et al., 2023; Hou et al., 2020; Devers et al., 2007).

Additionally, I include variables related to firm fundamentals and other financial characteristics. Firm size is another important determinant of CEO compensation since risk-averse CEOs prefer their pay tied to more stable factors like firm's size rather than performance (Tosi et al., 2000; Berrone and Gomez-Mejia, 2009; Claude et al., 2017). *Size* is measured as the logarithm of a firm's total assets. *B/M* (the logarithm of the book-to-market ratio), *Leverage* (the ratio of the sum of long-term debt and debt in current liabilities to total assets), and *Dividends* (total amount of dividends scaled by net income) are included as they are potentially related to firms' decisions about ESG-oriented management practices (Cohen et al., 2023).

Return and *Volatility* are calculated based on monthly returns and closing prices of the previous fiscal year obtained from the CRSP Monthly Stock File database. The number of shares outstanding and stock price needed to calculate the book-to-market ratio are also obtained from CRSP data. Information on firm fundamentals, including company-specific fiscal year-end dates, is collected from Compustat North America.

I also introduce variables that account for CEO power and influence on compensation structures. The first variable is *CEO tenure*, defined as the duration of the current CEO's tenure in their position at the company (Berrone and Gomez-Mejia, 2009). Tenure influences CEOs' risk-taking behavior and firm-specific expertise, and it is a practical consideration when designing compensation packages as it is easily observable (Hou et al., 2020). The second measure, *duality*, indicates whether the CEO also serves as the chair of the board. The duality status is identified based on the chief executive's title listed in Compustat ExecuComp and is represented as a dummy variable: it takes the value of 1 if the CEO

Table 2

	N	Mean	SD	25%	Median	75%
Pay ratio	27,664	0.463	0.289	0.246	0.538	0.687
Total pay	27,733	8.266	1.200	7.642	8.421	9.034
Return	35,124	0.146	0.856	−0.147	0.080	0.322
Volatility	35,124	0.111	0.087	0.067	0.094	0.132
Size	35,124	7.795	1.680	6.639	7.713	8.883
B/M	35,124	−0.919	0.868	−1.374	−0.839	−0.351
ROA	35,124	0.054	0.132	0.030	0.058	0.095
Leverage	35,124	0.275	0.236	0.102	0.255	0.392
Dividends	35,124	0.355	6.092	0.000	0.000	0.338
Tenure	27,733	4.972	3.717	2	4	7
Duality	27,733	0.429	0.495	0	0	1
CEO share	22,105	2.349	5.931	0.200	0.619	1.755

Descriptive Statistics of Dependent and Control Variables. The table reports summary statistics of the dependent and control variables. *Pay ratio* and *Total pay* are the dependent variables used to test the hypotheses of this paper. *Pay ratio* represents the proportion of CEOs' equity-based incentives in their total compensation. *Return, volatility*, and *ROA* represent the firms' financial performance. *Return* and *volatility* are calculated from monthly stock returns. *Size, B/M, Leverage*, and *Dividends* are measures of firm fundamentals. *Size* and *B/M* are measured as the natural log of total assets in millions of dollars and book-to-market ratio, respectively. *Tenure, Duality*, and *CEO share* reflect firm governance and indicate the CEOs' influence over their own compensation.

also holds the position of board chair and 0 otherwise. This controls for the influence of the CEO on board decisions on compensation (Carpenter, 2000; Berrone and Gomez-Mejia, 2009). The third variable related to CEO governance is *CEO share*, which corresponds to the percentage of the firm's shares owned by the CEO (Berrone and Gomez-Mejia, 2009). Previous studies have shown that a CEO's stock ownership affects their compensation, risk-taking behaviors, strategy, and firm performance (Sanders, 2001; Hou et al., 2020; Berger and Yermack, 1997). Data on CEO ownership, tenure, and title are sourced from Compustat ExecuComp database.

	ER	CE	CE^{Tran}	CE^{Phy}	OER	Return	Volatility	Size	B/M	ROA	Leverage	Dividends	Tenure	Duality	CEO share
ER	1														
CE	0.945	1													
CE^{Tran}	0.866	0.919	1												
CE^{Phy}	0.599	0.627	0.274	1											
OER	0.545	0.243	0.212	0.169	1										
Return	-0.009	-0.006	0.003	-0.022	-0.011	1									
Volatility	-0.089	-0.077	-0.038	-0.114	-0.066	0.359	1								
Size	0.213	0.185	0.178	0.103	0.157	-0.039	-0.24	1							
B/M	-0.006	-0.005	-0.004	-0.005	-0.005	0.003	-0.006	0.014	1						
ROA	0.002	-0.007	-0.017	0.014	0.023	0.062	-0.189	0.159	-0.001	1					
Leverage	0.058	0.048	0.022	0.074	0.049	-0.029	0.045	0.276	0.009	-0.02	1				
Dividends	0.010	0.011	0.006	0.015	0.001	-0.005	-0.017	0.022	-0.001	-0.015	0.02	1			
Tenure	0.001	0.003	0.004	0.002	-0.005	0.011	-0.035	0.022	-0.013	0.028	-0.016	0.005	1		
Duality	0.058	0.046	0.035	0.044	0.053	-0.005	-0.066	0.139	0.001	0.043	-0.026	0.004	0.264	1	
CEO share	-0.091	-0.076	-0.072	-0.043	-0.076	0.006	0.065	-0.214	-0.004	-0.003	-0.1	-0.005	0.129	0.169	1

Table 3. Correlations between climate risk measures and firm characteristics

5 Results

I analyze how a firm's climate risk exposures, measured by the attention given to climate change topics in earnings calls, affect CEO compensation. The aim is to investigate (1) whether climate change is being incorporated into the firm's CEO pay decision process, and (2) how managers assess the impact of climate risks on the firm's market value and risk premium. To this end, l estimate the following fixed-effects predictive regression:

$$Compensation_{i,t+1} = \sum_{\ell} \beta_\ell Measures^{\ell}_{i,t} + \gamma' \mathbf{X}_{i,t} + \lambda_t + \delta_j + \varepsilon_{i,t}, \tag{8}$$

where the vector $\mathbf{X}_{i,t}$ includes firm-specific control variables known to affect CEO compensation, such as $Return_{i,t}$, $Volatility_{i,t}$, $Size_{i,t}$, and $ROA_{i,t}$, as well as corporate governance variables like $Tenure_{i,t}$, $Duality_{i,t}$, and $CEO\ share_{i,t}$. The variables λ_t and δ_j represent time and industry fixed effects, respectively. $Compensation_{i,t+1}$ is the CEO's one-year-ahead total compensation (*Total pay*) or proportion of stock-based incentives (*Pay ratio*). If managers view climate risks as having a material impact on firms' market performance, they would adjust the proportion of stock-based incentives accordingly (Hypotheses 1a and 2a). Similarly, the board of directors may either offer higher incentives for managing increased risk or hold executives responsible for declining profitability (Hypotheses 1b and 2b).

$Measures^{\ell}_{i,t}$ represents the earnings call-based risk exposure measures constructed by BERT for the class label $\ell \in \{Environmental, Transition, Physical, Other\}$. Specifically, each ℓ indicates a topic discussed in earnings calls, and $Measures^{\ell}_{i,t}$ is the proportion of discussion dedicated to the respective topic in earnings calls conducted by firm i during year t. I test three sets of variables:

1. ($ER_{i,t}$). This corresponds to $\ell = Environmental$. $ER_{i,t}$ is obtained through equation (3) and denotes firm i's overall environmental risk at fiscal year t. This does not distinguish climate change-related risks and other environmental risks.

2. ($CE_{i,t}$, $OER_{i,t}$), which decomposes $ER_{i,t}$ into climate risks and non-climate change-related environmental risks to focus on the impact of climate risk on the compensation variables. This corresponds to $\ell \in \{Transition, Physical, Other\}$, but CE does not distinguish transition and physical risks.

3. ($CE_{i,t}^{Tran}, CE_{i,t}^{Phy}, OER_{i,t}$). Relevant classes are $\ell \in \{Transition, Physical, Other\}$. The first two variables are decompositions of $CE_{i,t}$, differentiating exposure measures for transition and physical risks. These measures are derived from equations (6) and (7) and serve as the main explanatory variables of the analysis.

5.1 Main results

I first test Hypotheses 1a and 2a using the proportion of stock-based incentives in total compensation as the dependent variable. Table 4 reports the estimates without industry fixed effects in columns (1)-(3), and with all fixed effects in columns (4)-(6). The coefficients of the control variables in Table 4 are directionally consistent with expectations from previous literature across all the specifications. Financial performance, particularly annual stock return, return volatility, and firm size are strongly significant and found to be the main determinants of stock awards.

Columns (4)-(6) present the main results. In column (4), overall environmental risk $ER_{i,t}$ has a significant negative impact on the proportion of CEO's stock-based compensation. Column (5) shows that this effect is primarily driven by climate risk $CE_{i,t}$ rather than $OER_{i,t}$. This suggests that other environmental risks, such as recycling, waste, or pollution, are not considered as factors that could affect stock prices. However, it is important to note that $OER_{i,t}$ is a byproduct of the classification algorithm, designed primarily to improve the accuracy of transition and physical risk measures, and did not undergo the same calibration process as the other classes. Consequently, it may not accurately reflect exposure to other environmental risks[6].

Column (6) reports the results using topic-based measures of climate risks: transition risk (CE^{Tran}) and physical risk (CE^{Phy}). Both types of climate risks are economically significant and decrease pay ratio for the following fiscal year. These findings support Hypotheses 1a and 2a, which posit that exposure to climate risks would lead to a reduction in the proportion of stock-based compensation. Specifically, for a one standard deviation increase in exposure to each risk type, managers decrease the proportion of stock-based incentives by approximately 0.54 percentage points for physical risk and 0.61 percentage points for transition risk. This corresponds to changes of -1.06% and -1.19%, respectively, in the average pay ratio for the next fiscal year. In other words, when climate crisis exposure increases by one standard deviation, about 1% of the amount previously received in restricted stocks or stock options is replaced with fixed compensation.

It is particularly noteworthy that physical risk exposure shows a highly significant and negative impact on pay ratio. This finding contrasts with previous studies by Stroebel and Wurgler (2021), Hong, Li, and Xu (2019), Faccini, Martin, and Skiadopoulos (2023), and Sautner et al. (2023b), which found little evidence of physical risk being priced in the market. Moreover, this result diverges from the positive impact of physical risks observed in the CDS market by Kolbel et al. (2023), who attribute it to the uncertainty reduction effect. Instead, it is consistent with the findings of Kruttli, Tran, and Watugala (2023), who reported increased volatility in the options market following natural disasters. This result suggests a disparity between how market participants and corporate insiders perceive climate risks, with managers reacting in a manner similar to participants in the derivatives market.

Columns (1)-(3) present results from one-way fixed effect regressions without industry fixed effects. As Sauter et al. (2023a) and Bolton and Kacperczyk (2021) have pointed out, firms within the same industry are likely to have similar exposures. Therefore, I aimed

[6]More precisely, some of its influence may have been captured by the transition risk and physical risk measures

Table 4

	Dependent variable: *Stock-based compensation*					
	(1)	(2)	(3)	(4)	(5)	(6)
ER	-0.345^{***}			-0.121^{***}		
	(0.027)			(0.035)		
CE		-0.373^{***}			-0.161^{***}	
		(0.032)			(0.039)	
CE^{Tran}			-0.185^{***}			-0.135^{***}
			(0.039)			(0.043)
CE^{Phy}			-0.849^{***}			-0.236^{***}
			(0.075)			(0.087)
OER		-0.214^{***}	-0.196^{**}		0.051	0.048
		(0.081)	(0.081)		(0.087)	(0.087)
Return	0.016^{***}	0.016^{***}	0.016^{***}	0.015^{***}	0.015^{***}	0.015^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Volatility	-0.169^{***}	-0.169^{***}	-0.177^{***}	-0.167^{***}	-0.167^{***}	-0.167^{***}
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Size	0.041^{***}	0.041^{***}	0.040^{***}	0.047^{***}	0.047^{***}	0.047^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(B/M)	−0.001	−0.001	−0.001	−0.001	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ROA	−0.001	−0.002	0.0005	0.017	0.018	0.018
	(0.014)	(0.014)	(0.013)	(0.013)	(0.014)	(0.014)
Leverage	-0.050^{***}	-0.051^{***}	-0.046^{***}	−0.005	−0.005	−0.005
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Dividends	0.023	0.025	0.040	0.123	0.123	0.129
	(0.265)	(0.264)	(0.265)	(0.257)	(0.257)	(0.257)
Tenure	−0.0004	−0.0004	−0.0004	-0.001^{**}	-0.001^{**}	-0.001^{**}
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Duality	-0.011^{***}	-0.011^{***}	-0.011^{***}	-0.006^{*}	-0.006^{*}	-0.006^{*}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
CEO share	-0.007^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}	-0.007^{***}
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.1364	0.1365	0.1385	0.1541	0.1543	0.1544
N	22,074	22,074	22,074	22,074	22,074	22,074

Effect of Climate Risk Exposures on CEO Stock-based Compensation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. All regressions include time fixed effects. In the regressions for columns 4 through 6, industry-fixed effects are added and standard errors are clustered at the industry level.

Table 5

	Dependent variable: *Total compensation*					
	(1)	(2)	(3)	(4)	(5)	(6)
ER	-1.766^{***}			-0.595^{***}		
	(0.096)			(0.121)		
CE		-1.972^{***}			-0.725^{***}	
		(0.112)			(0.137)	
CE^{Tran}			-1.383^{***}			-0.648^{***}
			(0.138)			(0.151)
CE^{Phy}			-3.389^{***}			-0.902^{***}
			(0.266)			(0.305)
OER		-0.810^{***}	-0.753^{***}		-0.039	-0.048
		(0.287)	(0.287)		(0.302)	(0.302)
Return	0.084^{***}	0.084^{***}	0.084^{***}	0.078^{***}	0.078^{***}	0.078^{***}
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
Volatility	-0.353^{***}	-0.348^{***}	-0.374^{***}	-0.438^{***}	-0.437^{***}	-0.438^{***}
	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)	(0.080)
Size	0.370^{***}	0.370^{***}	0.368^{***}	0.402^{***}	0.401^{***}	0.401^{***}
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
B/M	0.0003	0.0003	0.0002	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ROA	0.232^{***}	0.229^{***}	0.235^{***}	0.278^{***}	0.279^{***}	0.280^{***}
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)
Leverage	0.069^{***}	0.068^{***}	0.081^{***}	0.165^{***}	0.165^{***}	0.166^{***}
	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.027)
Dividends	-0.449	-0.428	-0.386	0.604	0.619	0.624
	(0.936)	(0.936)	(0.935)	(0.897)	(0.897)	(0.897)
Tenure	0.014^{***}	0.014^{***}	0.014^{***}	0.013^{***}	0.013^{***}	0.013^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Duality	0.070^{***}	0.069^{***}	0.070^{***}	0.050^{***}	0.049^{***}	0.049^{***}
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
CEO share	-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.025^{***}	-0.025^{***}	-0.025^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
R^2	0.408	0.408	0.409	0.431	0.431	0.431
N	22,105	22,105	22,105	22,105	22,105	22,105

Effect of Climate Risk Exposures on CEO Total Compensation. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. Standard errors are in parentheses. All regressions include time fixed effects. In the regressions for columns 4 through 6, industry-fixed effects are added and standard errors are clustered at the industry level.

to compare these results with those in columns (4)-(6), which include all fixed effects, to determine if there are significant within-industry differences in the same industry sector. Comparing columns (2)-(3) with (5)-(6), the introduction of industry fixed effects weakens the impact of *OER* (environmental issues other than climate risks) and *Leverage*, while strengthening the influence of *Tenure*. However, the significance of climate risks remains unchanged. This aligns with the substantial within-industry variation observed in Table A.3, providing evidence that individual firms within the same industry have different exposures, resulting in significant firm-specific effects. These findings support the rationale for constructing firm-specific measures.

Table 5 tests the impact of climate risk exposures on the total compensation. Columns (4)-(6) show that annual return, volatility, and total assets consistently and significantly influence the CEO's total pay, as seen in Table 4, supporting existing findings in the CEO compensation literature. *OER* remains insignificant for total pay. Columns (5) and (6) reveal that both types of climate risks negatively affect total pay in the next fiscal year. These results lend support to Hypothesis 2a. However, the strong statistical significance of physical risks in column (6) rejects Hypothesis 2b, which postulates that physical risks would not affect total compensation. The magni A one standard deviation increase in physical risk exposure leads to a 2.08% decrease in total pay, differing by less than one percentage point from the 2.93% decrease associated with transition risks.

In the context of my hypotheses that assume the board of directors has greater influence over total compensation decisions, these findings suggest that companies with higher exposure to climate change are more proactively responding to structural changes in the industry and incorporating climate risks into their CEO pay policies. Notably, this indicates that CEOs are being held accountable for managing unpredictable risks such as natural disasters.

However, these results may also support the environmental stewardship theory proposed by Francoeur et al. (2017). As highlighted in their research, firms committed to environmental sustainability tend to pay their CEOs less, and CEOs voluntarily accept lower compensation in pursuit of moral satisfaction. Thus, from the environmental stewardship perspective, an alternative interpretation theory is possible: companies with higher climate change exposure may be voluntarily or involuntarily pursuing transformation into environmentally friendly firms. In this process, CEOs may willingly accept (or be pressured by social expectations and boards to accept) lower compensation.

5.2 Subsample analysis

As Giglio, Kelley, Stroebel (2021) and Li et al. (2024) have noted, climate change likely began to be perceived as a significant financial risk following political events that led to regulations and raised social awareness. Such events, acting as regulatory shocks, likely triggered more substantial changes in transition risks rather than physical risks (Hypotheses 3a and 3b). To test this, I conducted an analysis again by dividing the sample into periods before and after the 2015 Paris Climate Agreement, which sparked a strong global shift in climate change awareness through transnational cooperation.

The results for the subsample analysis are presented in Table 6. There is partial evidence in favor of Hypothesis 3a. Panel (a) shows the expected variation in the coefficient for transition risks over time. The effect of transition risks on pay ratio is statistically insignificant in the early period but becomes significant with a larger magnitude after the Paris Climate Agreement. However, surprisingly, panel (b) indicates that CEO total pay responds significantly to transition risks in both periods. Nevertheless, the Paris Agreement is found to strengthen the magnitude of the effect. In the early period (before the Paris Agreement), a one standard deviation increase in transition risk exposure decreased total pay by 2.09%, while afterwards, it reduced total pay by 3.2%, demonstrating the increased risk-perception effect following the Paris Agreement.

Meanwhile, Hypothesis 3b, which states that the effect of physical risks would remain constant throughout the sample period, is rejected in both panels (a) and (b). The coefficient

Table 6

Panel (a) Stock-based Compensation

	Before Paris Agreement			After Paris Agreement		
	(1)	(2)	(3)	(4)	(5)	(6)
ER	-0.078			-0.147^{***}		
	(0.051)			(0.049)		
CE		-0.107			-0.169^{***}	
		(0.095)			(0.056)	
CE^{Tran}			-0.102			-0.242^{***}
			(0.069)			(0.065)
CE^{Phy}			-0.103			-0.237^{**}
			(0.125)			(0.139)
OER		0.174	0.174		-0.056	-0.186
		(0.132)	(0.133)		(0.123)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.154	0.202	0.202	0.123	0.123	0.168
N	11,854	11,854	11,854	10,220	10,220	10,220

Panel (b) Total Compensation

	Before Paris Agreement			After Paris Agreement		
	(1)	(2)	(3)	(4)	(5)	(6)
ER	-0.549^{***}			-0.579^{***}		
	(0.174)			(0.172)		
CE		-0.716^{***}			-0.702^{***}	
		(0.199)			(0.197)	
CE^{Tran}			-0.552^{**}			-0.614^{***}
			(0.242)			(0.214)
CE^{Phy}			-0.527			-0.983^{**}
			(0.431)			(0.461)
OER		0.134	-0.243		-0.074	-0.078
		(0.432)	(0.457)		(0.431)	(0.431)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.439	0.440	0.464	0.376	0.376	0.376
N	11,868	11,868	11,868	10,237	10,237	10,237

Table 7

Panel (a) Stock-based Compensation

	Year < 2010	2010 ≤ Year < 2015	Year ≥ 2015
	(1)	(2)	(3)
CE^{Tran}	-0.0542	-0.1540^{*}	-0.1422^{**}
	(0.1041)	(0.0831)	(0.0611)
CE^{Phy}	-0.3109	-0.1524	-0.2581^{**}
	(0.2176)	(0.1446)	(0.1311)
OER	-0.2671	0.3418^{**}	-0.0577
	(0.2230)	(0.1502)	(0.1228)
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.135	0.155	0.123
N	4,997	6,857	10,220

Panel (b) Total Compensation

	Year < 2010	2010 ≤ Year < 2015	Year ≥ 2015
	(1)	(2)	(3)
CR_TR2	-0.6134^{*}	-0.6978	-0.6138^{***}
	(0.3571)	(0.4264)	(0.2138)
CR_PR2	-1.2891^{*}	-0.7261	-0.9932^{**}
	(0.7468)	(0.6911)	(0.4606)
OER	-0.7559	0.5836	-0.0826
	(0.7652)	(0.5222)	(0.4314)
Controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.4346	0.4340	0.3760
N	5,004	6,864	10,237

for physical risks becomes significant only after the Paris Agreement for both pay ratio and total pay. This suggests that, following the Paris Agreement, physical shocks induced by climate change began to be perceived as risks rather than mere misfortunes by firms and managers, with their frequency and intensity likely increased in the later period.

In order to provide more elaborate tests on how the effect of climate risks evolves over time, I repeated the analysis by dividing the sample into three subsamples, considering both the introduction of the SEC climate change guidelines in 2010 and the Paris Agreement in 2015.

Table 7 reports the results of the subsample regressions. While there is still no support for Hypothesis 3b, the results provide stronger evidence for Hypothesis 3a. As panel (a) suggests, with respect to pay ratio, it becomes more evident that the economic significance of transition risks has increased over time. On the other hand, in the test of total pay (panel (b)), the results differ slightly. The coefficients for both transition and physical risks, instead of becoming gradually significant, are weakly significant in the earliest period (before 2010) and insignificant during the middle period (between 2010 and 2015). The effect becomes significant again after 2015 (the Paris Agreement). In the earliest period, a one standard deviation increase in transition risk leads to a 2.33% decrease in total pay, while in the latest period, it results in a 3.21% decrease, indicating a change in magnitude. Overall, the results in Table 7 align more closely with Hypothesis 3a, providing evidence that the influence of transition risks on both CEO stock-based incentives and total compensation changes over time.

6 Conclusion

This study quantifies firm-level climate risk exposure using a state-of-the-art language model applied to earnings conference call transcripts. With the success of transformer architecture, neural network models like BERT (for natural language understanding) and ChatGPT (for natural language generation) have become mainstream in recent NLP approaches. I utilize one of the most advanced BERT-based models, DeBERTa V3, to develop a novel set of distinct measures for transition and physical climate risks.

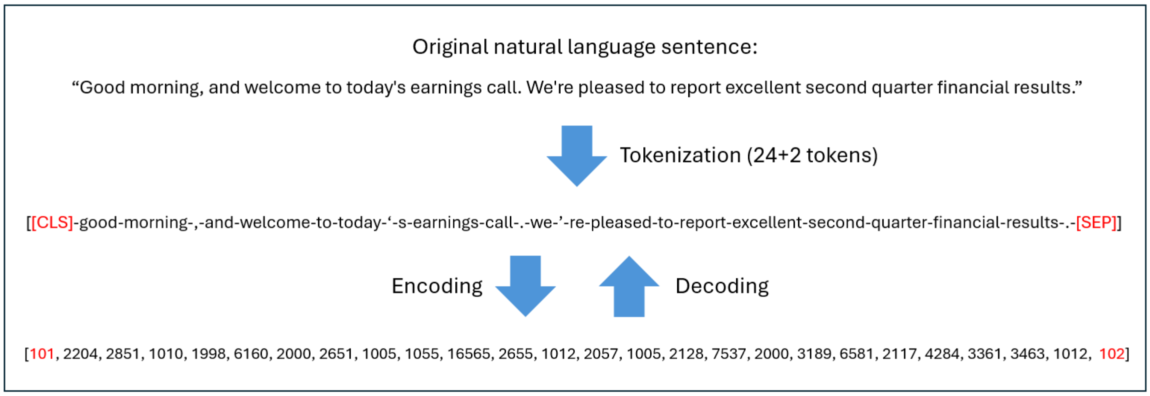
Using these topic-based climate risk measures constructed by the language model, I find significant negative correlations between climate risks and CEO compensation. This highlights how recent language models can facilitate the analysis of textual data, contributing to research in climate finance and other fields that traditionally lack reliable quantitative data.

My evidence suggests that as firms' exposure to climate risks increases, they pay their CEOs less total compensation. When companies dedicate a larger proportion of their entire earnings call discussions to climate change, they are not merely "greenwashing" but genuinely view climate risks as actual threats and are committed to addressing them. Notably, I find that stock-based incentives are replaced with fixed salaries when physical risks rise, suggesting that firm insiders anticipate the negative impact of physical climate risks on future stock prices. Furthermore, the influence of climate risks on CEO compensation has evolved in tandem with societal awareness of climate change, becoming economically significant after the Paris Climate Agreement.

Appendix

A.1 Tokenizing Sentences

Panel (a)



Panel (b)

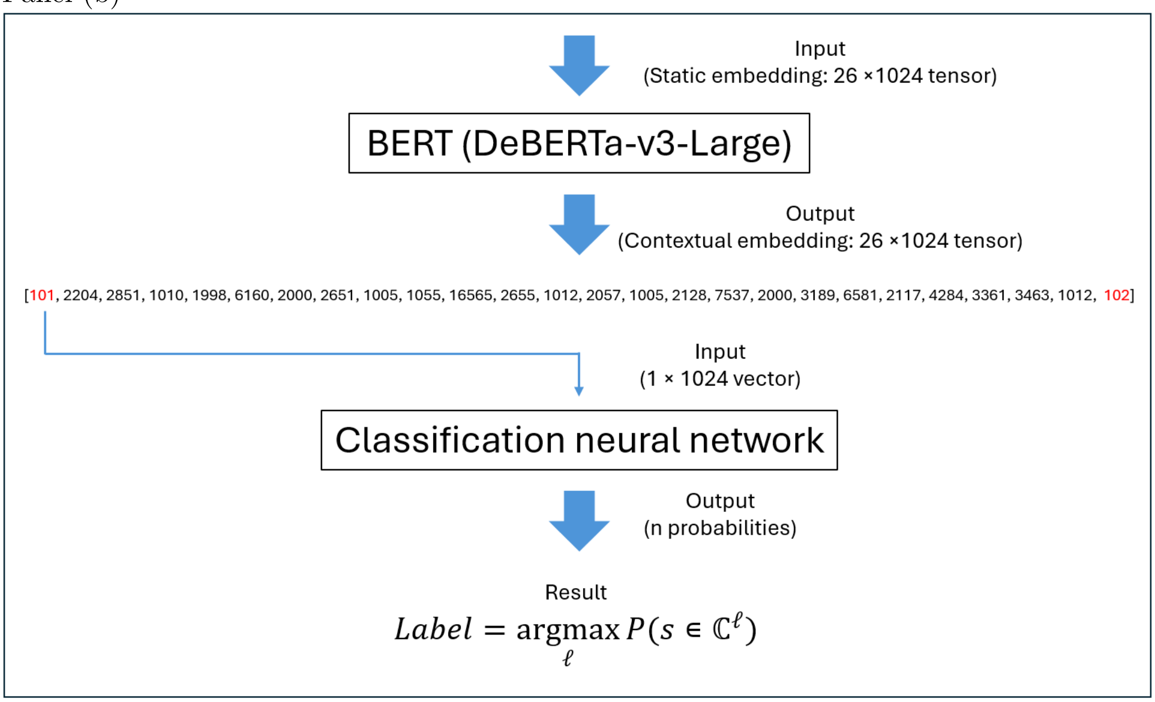


Figure A.1 Illustration of sentence tokenization and classification algorithm. s represents the natural language sentence discussed in the earnings call transcript. $\mathbb{C}$ is a space of natural language sentences, and $\mathbb{C}^{\ell}$ is its subspace for a specific class ℓ.

A.2 Details on BERT

Let $\mathbb{C}$ be the space, or set, of the entire natural language sentences. Assume that $\mathbb{C}$ can be partitioned according to *class* or label of sentences. Then $\mathbb{C}^{Gen}$ and $\mathbb{C}^{Env}$ are regions or subsets of $\mathbb{C}$, and general sentences and sentences mentioning environmental topics belong to the regions, respectively. $\mathbb{C}^{Env}$ is partitioned further as $\mathbb{C}^{Tran}$, $\mathbb{C}^{Phy}$, and $\mathbb{C}^{Other}$, which are regions for sentences relevent to transition risks, physical risks, and other environmental risks, respectively.

Suppose that firm i holds a conference call at period t, and the transcript contains $J_{i,t}$ sentences. BERT calculates the probabilities that each sentence $s_j^{i,t}$, $j = 1, \ldots, J_{i,t}$, belongs to each class. The exposure measures are calculated as

$$ER_{i,t} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6) \times 1(\max P_2(s_j^{i,t}) > 0.4) \Big] \tag{9}$$

$$CE_{i,t} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6) \times 1(\max P_2(s_j^{i,t}) > 0.4) \times 1(\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) \in \{Tran, Phy\}) \Big] \tag{10}$$

$$OER_{i,t} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1\big(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6\big) \times 1\big(\max P_2(s_j^{i,t}) > 0.4\big) \times 1\big(\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Other\big) \Big] \tag{11}$$

$$CE_{i,t}^{Phy} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[1(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6) \times 1(\max P_2(s_j^{i,t}) > 0.4) \times 1(\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Phy) \Big] \tag{12}$$

$$CE_{i,t}^{Tran} = \frac{1}{J_{i,t}} \sum_{j=1}^{J_{i,t}} \Big[\Big\{ 1(P_1(s_j^{i,t} \in \mathbb{C}^{Env}) > 0.6) \times 1(\max P_2(s_j^{i,t}) > 0.4) \Big\}$$
$$\times \Big\{ 1(\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Tran) + 1(\arg\max_{\ell} P_2(s_j^{i,t} \in \mathbb{C}^{\ell}) = Phy) \times 1\big(P_3(s_j^{i,t} \in \mathbb{C}^{Tran}) > 0.9\big) \Big\} \Big], \tag{13}$$

where P_1, P_2, and P_3 are probabilities calculated by BERT classifiers trained differently as mentioned in the above section.

A.3 Industry-level Climate Risk Exposure Measures

Table A.3

Panel (a) CE – All environmental risks

GICS Code	Industry	N	Mean	SD	Median
551050	Independent Power and Renewable Electricity Producers	135	22.98	10.93	20.87
551010	Electric Utilities	485	22.47	11.12	20.89
551030	Multi-Utilities	267	17.98	8.57	16.57
551020	Gas Utilities	239	15.48	9.97	12.83
201040	Electrical Equipment	606	13.09	12.20	9.34
551040	Water Utilities	91	12.32	7.20	11.99
201030	Construction & Engineering	483	9.28	8.58	6.68
251020	Automobiles	118	9.10	8.53	5.95
151020	Construction Materials	99	8.71	4.06	7.94
151010	Chemicals	1,061	8.24	8.78	5.68

Panel (b) CE^{Tran} – Transition risks

GICS Code	Industry	N	Mean	SD	Median
551050	Independent Power and Renewable Electricity Producers	135	19.77	11.43	17.95
551010	Electric Utilities	485	13.80	10.89	11.23
201040	Electrical Equipment	606	10.93	12.30	5.44
551030	Multi-Utilities	267	9.49	7.86	7.67
251020	Automobiles	118	7.99	8.52	4.83
551020	Gas Utilities	239	5.88	8.34	1.67
251010	Automobile Components	422	5.68	8.12	2.28
201030	Construction & Engineering	483	4.61	7.97	0.99
151010	Chemicals	1,061	3.49	7.16	0.84
101020	Oil, Gas & Consumable Fuels	2,377	2.99	7.95	0.10

Panel (c) CE^{Phy} – Transition risks

GICS Code	Industry	N	Mean	SD	Median
551020	Gas Utilities	239	8.24	6.02	7.16
551010	Electric Utilities	485	6.72	5.15	5.55
551030	Multi-Utilities	267	6.61	4.17	5.91
151020	Construction Materials	99	6.53	4.21	5.87
551040	Water Utilities	91	5.69	5.42	4.37
201030	Construction & Engineering	483	3.21	3.53	2.24
255010	Distributors	107	2.91	3.89	1.00
551050	Independent Power and Renewable Electricity Producers	135	2.59	2.28	2.20
201020	Building Products	477	2.54	2.93	1.48
203030	Marine Transportation	90	2.52	3.06	1.58

(Continued)

(Continued)

Panel (d) OER – Other environmental risks

GICS Code	Industry	N	Mean	SD	Median
551040	Water Utilities	91	5.84	3.54	5.41
202010	Commercial Services & Supplies	974	4.80	7.47	0.75
151030	Containers & Packaging	307	3.22	3.57	2.12
151010	Chemicals	1,061	3.17	4.21	1.81
551010	Electric Utilities	485	2.91	2.56	2.15
551030	Multi-Utilities	267	2.61	2.19	2.13
151040	Metals & Mining	640	2.08	2.57	1.15
151050	Paper & Forest Products	124	2.04	1.85	1.51
551020	Gas Utilities	239	1.79	2.36	1.25
201020	Building Products	477	1.73	2.63	0.66

Industry Distribution of Climate Risk Measures. This table presents climate risk exposure measures for the top 10 industries, with data compiled at the firm-year level across GICS industries. Industries are ordered by the average values of the risk measures. All measures are average values of the earnings calls during the fiscal year. This reveals significant variation within industries, which indicates that firms experience different levels of impact (benefit or suffer) from climate change.