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Climate Regulatory Risks and Executive Compensation: Evidence from State SCAP Finalization

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Abstract

Different U.S. state governments have begun to adopt climate adaptation strategies and action plans to prepare for and combat the significant threats of climate change. The finalization of these strategies and action plans results in a state-level adaptation plan—the SCAP. We find that the SCAP finalization leads to a significant increase in perceived climate regulatory risks faced by local firms and a significant reduction in their CEO pay (and other executive pay). Moreover, the negative effect of the SCAP finalization on executive pay is found to be greater for local firms in the states with less detailed goals/objectives in their SCAPs, further suggesting that the SCAP finalization reduces CEO pay through increasing the perceived climate regulatory risks faced by local firms. The effect of the SCAP finalization on CEO pay is also found to be stronger for treated firms more sensitive to climate regulatory risks or facing greater external threats, but weaker for treated firms with more entrenched or powerful CEOs. Finally, after the SCAP finalization, executive pay of local firms becomes less sensitive to corporate financial performance and stock volatility, but more likely to be linked to corporate environmental performance.

Keywords: SCAP Finalization; Executive Compensation; Climate Regulatory Risks

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1. Introduction

This paper investigates the effect of an increase in perceived climate regulatory risks due to the finalization of the U.S. state-level climate action plans (SCAPs) on corporate executive compensation. Climate change such as global warming in the past decades have posed significant threats to sustainable economic growth and human lives. Governments around the world are increasingly aware of the climate crisis and are taking coordinated effort and adopting policies and regulations to combat climate changes (e.g., the United Nations Framework Convention on Climate Change, the Kyoto Protocol, and the Paris Agreement). As a result, firms and their executives are facing significant climate regulatory risks and are under increasing pressures to adopt green technologies and reduce carbon emissions and pollutions. How the increased climate regulatory risks find their way into the incentives of corporate executives and affect the level and structure of executive compensation is an important research question. We address this research question using the climate regulatory risk materialization through the finalization of SCAPs in different states in the U.S. over the 1994-2018 period.

Different U.S. state governments have begun to adopt adaptation strategies and action plans to prepare for and combat the significant threats of climate change. The finalization of these adaptation strategies and action plans in a state leads to a state-level climate adaptation plan—the SCAP—that outlines recommendations, measures and goals to reduce emissions and to prepare for the impacts of climate change. Over the 2008-2020 period, 19 U.S. states finalized their SCAPs, with Florida, Maryland and Virginia being the first adopters in 2008 and North Carolina and Montana being the latest adopters in 2020. The finalization of the SCAP of a state sends a clear signal to local firms located in the state that the state government is serious and determined to take future actions, including legislative actions, to reduce emissions and combat climate change. Thus, the SCAP finalization in a state represents a materialization of climate regulatory risks on local firms in that state.

We begin our analysis by showing that the SCAP finalization in a state increases the attention of the market investors and local firms to climate-related topics, as proxied by an increase in Google search volume. Relative to the non-SCAP-adoption states, the SCAP-adoption states on average see an increase in climate-related Google search volume by 16 points.[1] We also find that the SCAP finalization in a state increases local firms' perceived

[1] The index value of the topic *climate* in other states will depend on their popularities relative to the state with the highest one. For example, the value of topic popularity in *climate* in California is 0.2, which is the highest among the states. Then its index value will equal 100. The value of topic popularity in climate in New York is 0.1, then its index value will equal 0.1/0.2 multiply by 100 which equals 50.

climate regulatory risk as proxied by the environment-related political risk measure from Hassan et al. (2019). Relative to control firms headquartered in the non-SCAP-adopting states, treated firms headquartered in the SCAP-adopting states on average experience an increase in perceived climate regulatory risk by 12% of the sample mean. These findings suggests that the SCAP finalization in a state clearly signals to the market investors and local firms that the state government is determined to take climate-related actions, which significantly increases local market attention to climate-related topics and the perceived climate regulatory risks faced by local firms in the state.

Next, employing a difference-in-differences (DiD) regression framework, we find that the SCAP finalization in a state on average results in a reduction of total CEO pay by about 5% for treatment firms headquartered in that state relative to control firms headquartered in other states. This finding is robust to controlling for a variety of firm, CEO and state characteristics, as well as state, firm and year fixed effects. The finding suggests that the increase in perceived climate regulatory risks through the SCAP finalization leads local firms' shareholders to expect higher future compliance costs of the firms and hence shareholders lower the executive pay of these firms to share the increased expected costs with corporate executives.

To examine whether the documented treatment effect of SCAP finalization on CEO pay is driven by potential non-parallel compensation trends before treatment year, we employ a dynamic DiD regression framework to identify the exact timing of the treatment effect. We find that the treatment effect of the SCAP finalization on CEO pay only exists from the treatment year onward but does not exist in any of the years prior to the treatment. This finding suggests that the parallel-trends assumption for the efficacy of the DiD approach is satisfied.

Moreover, to test the robustness of the main finding in a more rigorous identification strategy, we use a stacked-cohort DiD regression approach (e.g., Gormly and Matsa 2011). We match the treated firms in each SCAP-adoption event with control firms whose headquartered states never adopt SCAP but are neighbouring states of the SCAP-adoption state to form a cohort. We then stack all cohorts together for the DiD analysis. We use control firms in the neighbouring states of the SCAP-adoption state to ensure that the treated and control firms are subject to similar local economic dynamics (so that local market conditions do not drive the results). We continue to document a significantly negative treatment effect of SCAP finalization on CEO pay, with very similar economic magnitude as our baseline finding. A parallel-trend validation test is further conducted by visualizing the effects of the SCAP finalization on CEO pay where we allow the effects to vary each year. The figure explicitly shows that there is no indication of a decrease in executive pay before the SCAP-adoption year, and the effects can only be observed after adopting the SCAP. Thus, the parallel-trend assumption underlying the stacked-cohort DiD estimation is satisfied.

In addition, to ensure that our baseline finding is not driven by the differences in observable firm/CEO/state characteristics between the treatment and control firms, we carefully match treated and control firms based on all observable firm/CEO/state characteristics measured either in the year immediately prior to the treatment year, using the propensity-score-matching (PSM) technique. We continue to find a negative treatment effect of SCAP finalization on CEO pay with even larger magnitudes using the matched samples. Taken together, the evidence from the various DiD analyses suggests that the documented treatment effect of SCAP finalization on CEO pay is likely causal. Importantly, beyond CEO pay, we find that the SCAP finalization in a state also leads to an average reduction of *non-CEO* executive pay of the treated firms headquartered in the state by more than 6%, relative to the control firms headquartered in other states.

The SCAPs of different adopting states have different degrees of details. We conjecture that the less goals and objectives being specified in the SCAP of a state, the more uncertain local firms in that state should be about their state's SCAP implementation. That is, local firms in a state with higher SCAP uncertainty (less detailed goals/objectives in its SCAP) may only know that the state is determined to take climate-related actions but may not know in detail what actions (including legislative actions) the state will take, which can further increase the perceived climate regulatory risks of local firms. We find that it is indeed the case. The positive treatment effect of the SCAP adoption on firms' perceived climate regulatory risks is stronger for treated firms in the states with higher SCAP uncertainty. Moreover, because of the higher perceived climate regulatory risks induced by such SCAP uncertainty, those treated firms decrease more their executive compensation than the treated firms in states with clearer SCAPs, which lends further support to the interpretation that the SCAP finalization reduces CEO pay through increasing their perceived climate regulatory risks.

Having established a negative treatment effect of the SCAP finalization on executive compensation, we next conduct cross-sectional tests to better understand the heterogeneities in the treatment effect. If the increase in perceived climate regulatory risks through the SCAP finalization leads the shareholders of treated firms to lower executive pay to share the expected compliance costs with corporate executives, we conjecture that the negative treatment effect of SCAP finalization on executive pay should be stronger for firms that are believed to be more sensitive to climate regulatory risks ex ante. Consistent with this conjecture, we find that the treatment effect is indeed more pronounced for treated firms headquartered in the states with greater investor attention to climate-related issues, facing higher perceived climate regulatory risks, having more environmental concerns, receiving lower environmental ratings, facing greater environmental litigation risks, and/or holding more stranded assets in carbon-emitting industries.

Moreover, we expect that the treatment effect of the SCAP finalization on CEO pay should be weaker when the CEO is more entrenched or powerful, while it should be stronger when the firm is under greater external threats from the product markets and the market for corporate control. Consistent with the expectation, we find that the treatment effect is significantly weaker when the CEO has a long tenure or a significant share ownership in the firm. Moreover, the treatment effect is indeed significantly stronger for treated firms facing greater product market competition or higher hostile takeover threats.

Next, we examine whether the SCAP finalization in a state influences the composition of CEO pay for the local firms. If shareholders perceive the effect of the SCAP finalization to be only short-term, then they may just reduce cash-based CEO pay such as salaries and bonuses. However, if shareholders deem the SCAP impact to be long-term, then they may also decrease equity-based CEO pay such as restricted stock, options granted, as well as long-term incentive payouts. We find that both the cash-based and equity-based components of CEO pay decrease after the SCAP finalization, indicating that shareholders perceive the SCAP-induced materialization in climate regulatory risks to have both short-term and long-term impacts on treated firms.

We further investigate the effects of the increase in perceived climate regulatory risks through SCAP finalization on executive risk-taking incentives. To measure CEO risk-taking incentives, we follow Coles, Daniel, and Naveen (2006) and use CEO pay-performance sensitivity and CEO wealth-stock-volatility sensitivity, with higher values indicating greater incentives. We document negative and statistically significant treatment effects of SCAP finalization on both sensitivity measures, indicating that CEO pay becomes less dependent on the treated firm's financial profitability and stock volatility after SCAP finalization. That is, shareholders react to the increase in perceived climate regulatory risks by reducing executive risk-taking incentives, likely because shareholders become more conservative on corporate activities that, while profitable, may further increase the firm's future compliance costs.

Finally, if the SCAP finalization in a state increases local firms' perceived climate regulatory risks, we expect that shareholders of these firms should be more likely to link executive pay to future corporate environmental performance after the SCAP finalization in an effort to decrease expected future compliance costs.[2] To test this conjecture, we obtain firms' proxy statements (Form DEF 14A) that contain detailed information on executive compensation. We then use a machine learning framework, *Word2vec* (Mikolov et al., 2013), to obtain a list of environmental-performance-related keywords. To capture environmental-performance-linked executive compensation, we construct measures that capture the occurrence of an environmental-performance-related keyword that is surrounded by at least a compensation-related keyword and an executive-related keyword in the same DEF 14A statement. We find that the finalization of the SCAP results in a significant increase in executive pay being linked to corporate environmental performance. Relative to control firms, treated firms are on average 7% to 8% more likely to link their executive compensation to corporate environmental performance after the SCAP finalization.

This study contributes to the emerging literature studying the impact of climate regulatory risks on firms. For example, Bolton and Kacperczyk (2021) show that investors are demanding an equity risk premium from firms with higher total CO2 emissions for their exposure to carbon emission risk and that institutional investors implement exclusionary screening based on direct emission intensity in a few salient industries. Based on survey data, Krueger, Sautner, and Starks (2020) find that institutional investors believe that climate regulatory risks have begun to materialize and they consider risk management and engagement (rather than divestment) to be the better approach for addressing these risks.

Relatedly, Chava (2014) find that firms with environmental concerns (such as hazardous chemical, substantial emissions, and climate change concerns) have higher cost of equity and debt capital. Matsumura, Prakash, and Vera-Munoz (2014) find that the capital markets penalize all firms for their carbon emissions with lower firm value, but a further penalty is imposed on those firms that do not disclose emissions information. Sharfman and Fernando (2008) show that improved environmental risk management is associated with a lower cost of capital. Dowell, Hart, and Yeung (2000) find that U.S.-based multinational firms adopting a single stringent global environmental standard have higher market values.

We contribute to the literature by documenting that the increase in perceived climate regulatory risks through the SCAP finalization in different U.S. states leads to a reduction in corporate executive compensation. The effect is stronger for firms more sensitive to climate

[2] Flammer, Hong, and Minor (2019) show that linking corporate social responsibility to executive compensation leads to an increase in long-term orientation, an improvement of environmental performance, and an increase in green innovations. Similarly, Cohen et al. (2022) document a positive relation between the use of Environmental, Social and Governance (ESG) performance metrics in executive contracts and future corporate ESG performance.

regulatory risks and firms facing greater external threats, but weaker for firms with more entrenched or powerful CEOs. The increase in perceived climate regulatory risks also leads to a reduction in executive risk-taking incentives, but an increase in the occurrence of environmental-performance-linked executive compensation.

The remainder of the paper is organized as follows. Section 2 develops the hypothesis. Section 3 describes the data and sample and provides the summary statistics of the variables used in the study. Section 4 reports the empirical results. Section 5 concludes. The Appendix provides the definitions of all variables used in the study and their data sources, as well as additional empirical results.

2. Hypothesis Development

The natural disasters brought about by climate changes (e.g., bushfires in Australia, Greece and the U.S., flooding in China and Europe, sea level rises, etc.) have caught significant attention around the world. The ongoing climate crisis has led governments to coordinate their effort and adopt policies and regulations to combat climate changes. The most significant coordinated effort of countries around the world is the Paris Climate Accords (or the Paris Agreement) adopted in 2015, an international treaty covering climate change mitigation, adaptation and finance. It is well known that politicians in the U.S. have very different views on climate changes. For example, under President Donald J. Trump, the U.S. officially withdrew from the Paris Agreement in 2020. However, under President Joseph R. Biden Jr., the U.S. rejoined the Paris Agreement in 2021.

Across different U.S. states, state governments also have very different views on climate change. Over the 2008-2020 period, 19 states have finalized their state-level climate action plans. Florida, Maryland and Virginia are the first to finalize their SCAPs in 2008 and North Carolina and Montana are the latest to finalize its SCAP in 2020. Major states such as California and New York have also finalized their SCAPs (in 2009 and 2010, respectively). The finalization of the SCAP in a state clearly signals to local firms and their investors that the state government is very serious about climate change and is determined to take future climate-related actions, including legislative actions, if necessary, to reduce emissions and combat climate change. Such future actions can lead to an increase in expected future compliance costs of local firms as they may need to adopt green technologies and reduce their levels of carbon emissions and pollutions when operating in that state. Thus, the SCAP finalization in a state represents an increase in perceived climate regulatory risks on local firms in that state.

We conjecture that given the increase in perceived climate regulatory risks due to the SCAP finalization, shareholders of the treated firms may decrease their executive pay to share the expected compliance costs with corporate executives. Moreover, this negative effect of the SCAP finalization on executive pay should be more pronounced for those treated firms that are more sensitive to climate regulatory risks. In addition, the effect should be more (less) pronounced for firms facing greater external threats such as intense product market competition or hostile takeover pressures (firms having more entrenched or powerful CEOs). We formulate these conjectures into the following hypotheses.

Hypothesis 1: *The SCAP finalization in a state leads to a reduction in CEO pay for the local firms in that state.*

Hypothesis 2: *The negative effect of the SCAP finalization on CEO pay is more pronounced for treated firms who are more sensitive to climate regulatory risks or facing greater external threats, but less pronounced for treated firms with more entrenched or powerful CEOs*.

On the other hand, shareholders may perceive the SCAP finalization as a positive development that can help address the threats of climate change and lead to long-term sustainable firm growth and shareholder wealth creation. If that is the case, they may then increase corporate executive pay to compensate for the extra efforts that corporate executives need to incur to comply with the new climate actions. Therefore, the effect of the SCAP initialization in a state on executive compensation is unclear ex ante and warrants rigorous empirical investigation.

3. Data and Variable Construction

3.1. Sample Formation

States and communities around the U.S. have begun to prepare for the climate changes that are already underway. This planning process typically results in a document called an adaptation plan. The Adaptation Program at the Georgetown Climate Center (GCC) is one of the nation's leading sources of practical strategies for preparing and responding to the impacts of climate change.

In this study, we examine the effect of state-level climate action plans (SCAPs) on CEO compensation and risk-taking incentives. We code the *SCAP* indicator variable to be one if the firm is headquartered in a state that has finalized these plans, and zero otherwise. As shown in Table A2, over the 2008-2020 period, the GCC identifies in total 19 states that adopted the SCAPs with Florida (FL), Maryland (MD) and Virginia (VA) being the first adopters in 2008, while North Carolina (NC) and Montana (MT) being the latest adopter in 2020.[3] To account for the possibility that a number of firms relocated their headquarters outside a state, we rely on the information of *historical* headquarter states (rather than the current headquarter states in Compustat) compiled by Loughran and McDonald (2016).[4]

We start our sample construction with all Compustat firms for the 1994-2018 period, over which the historical state data is available.[5] Thus, 17 states finalized the SCAPs during, and 02 states (NC and MT in 2020) finalized the SCAPs post our sample period.

Finally, after requiring available data to construct CEO compensation (discussed in the next subsection), the *SCAP* indicator and all control variables in our baseline regression model, we have a baseline sample of 25,267 firm-year observations of 2,528 unique firms over the 1994-2018 period. Panel B of Table 1 reports the mean value of the *SCAP* dummy of 0.210 suggesting that about 21% of sample firm-years are headquartered in the SCAP-adopting states.

3.2. Variable Construction

3.2.1 Investor Attention to Climate-related Topics and Perceived Climate Regulatory Risk

We follow Da, Engelberg, and Gao (2011) and Gao, Ren, and Zhang (2020) to use Google Trend Search Volume Index (SVI) to measure investor attention. Specifically, we download annual SVI on the single search term *climate* for each state over the 2004-2018 period.[6] We then construct two dependent variables, the level of Google Search Volume Index on climate (*GSVI_CLIMATE*), and the change in the Google Search Volume Index on climate (Δ*GSVI_CLIMATE*), to proxy for investor awareness of climate-related topics.

Next, we use environmental-and-political risk measure from Hassan et al. (2019) to proxy for a firm's perceived climate regulatory risk (*ENV_RISK*).[7] Specifically, Hassen et al. (2019) use conference earnings call transcripts as text data and first construct an *overall* political risk measure for firms by counting the number of political-related words that are surrounded by risk synonyms in firms' transcripts. They further classify the political-related words into eight political topics, of which *environment* is one of the topics and is of our interest.

[3] Source: https://www.georgetownclimate.org/adaptation/plans.html
[4] The authors track the historical headquarter locations over the 1994-2018 period. Source: https://sraf.nd.edu/data/augmented-10-x-header-data/
[5] We donot extend the sample period further to avoid the recent pandemic impacts that could complicate our analysis.
[6] Google Trend (http://www.google.com/trends) provides historical data on search term frequency back to January 2004.
[7] The data can be downloaded here: https://sites.google.com/view/firmrisk/home. We thank Tarek Alexander Hassen and his research team for generously sharing the data.

They then generate eight topic-specific risk measures for each firm. We thus use the firm-level political risk in *environment* as proxy for a firm's perceived climate regulatory risk.[8]

3.2.2 CEO Compensation

Our main dependent variable of interest is CEO total compensation. Similar to Focke, Maug, and Niessen-Ruenzi (2017) and Hoi, Wu, and Zhang (2019), we source CEO pay information from ExecuComp. In particular, data item TDC1 in ExecuComp captures salary, bonus, value of restricted stocks granted, value of options granted, long-term incentive payouts, and other types of compensation. The key variable (*TOTAL_PAY*) is then defined as the natural logarithm of one plus the CEO total pay.

In addition to total pay, we also study the components of CEO compensation. We follow Dai, Rau, Stouraitis, and Tan (2020) and Huang, Jiang, Lie, and Que (2017), and focus on two distinct components, namely cash-based pay (*CASH_PAY*), which is calculated as the natural logarithm of one plus the sum of salary and bonus; and equity-based pay (*EQUITY_PAY*), which is computed as the natural logarithm of one plus the sum of option value, restricted stock value and long-term incentive payouts. We also examine the percentage of cash-based pay in total pay (*CASH_PAY_RATIO*), which is defined as the ratio of cash-based pay over total pay.

3.2.3 CEO Risk-taking Incentives

We employ two commonly used metrics that capture CEO risk-taking incentives. The first one is CEO pay-performance sensitivity, delta, which measures the change in the value of the option or restricted stock grants in a year, share holdings, and any accumulated restricted stock and option holdings for a 1% change in the stock price (Coles, Daniel, and Naveen, 2006; Liu and Mauer, 2011). The second one is sensitivity of CEO wealth to stock volatility, vega, which measures the change in the value of the CEO's option grant in a year and any accumulated option holdings for a 1% change in the annualized standard deviation of stock returns (Coles, Daniel, and Naveen, 2006; Liu and Mauer, 2011). We source the restricted stock and option value from ExecuComp, and stock returns from CRSP databases. Similar to the

[8] According to Hassen et al. (2019), the eight topics are: *economic policy & budget*, *environment*, *trade, institutions & political process*, *health care*, *security & defense*, *tax policy*, and *technology & infrastructure*. We believe that the political risk measure in environment is a good proxy for perceived climate regulatory risk because i) this measure is based on a firm's conference call transcript that is held by the CEO and thus should reflect his/her perception of the firm; ii) this measure focuses on the topic of environment, which is arguably climate related, and iii) it captures a firm's political risk, which is related to regulation.

construction of CEO pay variables, we take the natural logarithm of one plus delta (*DELTA*) and vega (*VEGA*) before performing the regression analysis.

3.2.4 Environmental Contracting

3.2.4.1 DEF 14A Filings and Word2vec Implementation

We use *Word2vec* (Mikolov et al., 2013), a machine learning framework, to construct a measure on whether corporate executive compensation is linked to environment (i.e., *environmental contracting*, or *E-pay*) based on a firm's proxy statement (SEC Form DEF 14A), which is an important material that a public-listed firm is required to provide before the annual meeting to help shareholders improve understandings on corporate governance related issues (e.g., voting procedure, nomination of board of directors and role of committees). Crucially, proxy statements provide detailed information on executive compensation, from which we can know the compensation structure of top executives, such as base salary, bonus, stock awards, and metrics used for performance-based incentives.

We first use a Python program to web scrape available DEF 14A filings from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database from 1994 to 2021. We then link the collected filings to ExecuComp database. We follow Loughran and McDonald (2014) and preprocess the raw text filings to remove unrelated sections and only keep the textual content.

Next, we follow Flammer, Hong, and Minor (2019) and use keyword approach to search through the annual proxy statement of each firm to identify whether firms adopt environmental contracting.[9] However, the pre-specified keywords may not be sufficient to capture the words that firms used to describe the environmental contracting. Thus, in spirit with Li et al. (2021), we decide to employ *Word2vec*, a machine learning architecture in natural language process (NLP), to quantify words into dense and low-dimension vectors. We can then compare the cosine similarities between word vectors to identify semantically similar words and thus further expand the environmental-related keyword list.

In essence, *Word2vec* model is based on the distributional hypothesis that "You should know a word by the company it keeps" (Firth, 1957). It proposes that words that are surrounded by close neighbouring words are likely to be semantically similar. The model will learn the

[9] Flammer, Hong, and Minor (2019) use the following environmental-related words as seed words: *energy efficiency*, *environmental compliance*, *environmental goals*, *environmental performance*, *environmental projects*, and *greenhouse gas emissions reductions*. They then manually search through the proxy statements of each firm to determine whether the executive compensation is linked to environment.

semantics/meaning of a word through recursively reading textual data (e.g., financial statements, textbook, and newspaper) and predicting its neighbouring words. The ultimate product of *Word2vec* is a vector representation of a word. We use *gensim* library in Python to train the *Word2vec* model. Our final self-trained model successfully quantifies each of the 642,365 unique word of the proxy statements into a 300-dimension word vector.[10]

3.2.4.2 Pre-specified Seed Words and Expanded Word List

First, we follow Flammer, Hong, and Minor (2019) and use their seven environmental-related words as seed words. In addition, we further complement with the following five words that are unambiguously related to environment but are not included in Flammer, Hong, and Minor (2019)'s keyword list: *climate risk*, *climate change*, *carbon emission*, *renewable energy*, and *air pollution*.[11]

Next, we feed the 12 seed words into the self-trained *Word2vec* model and obtain an expanded list of keywords that are having high cosine similarity scores with the seed words. A higher similarity score indicates that the word's meaning is closer to those of 12 environmental seed words. We follow Li et al. (2021) to select the top500 words that are having highest cosine similarity scores with $\overline{V_{SW}}$ as our expanded word list.

Nevertheless, we find that for those top500 words, not all of them are closely related to environment. For example, *human rights*, *diversity inclusion*, and *product safety* are included in the top500 word list but are not related to environment.[12] To reduce the Type I error (false positive), each of the co-authors manually screen the 500 words and determine whether they are related to environment or not. Our final keyword list, $\mathbb{E}$, has 398 environmental related words.[13]

3.2.4.3 Measuring the Adoption of Environmental Contracting

After obtaining an expanded list of environmental words from *Word2vec*, we then construct a measure to capture a firm's adoption of environmental contracting. The prior studies manually search pre-specified keywords in either Executive Compensation section or Compensation Discussion and Analysis (CD&A) section of each proxy statement to determine

[10] Please refer to Appendix B for more details about the data preprocessing and implementation of the *Word2vec* model.
[11] Panel A of Table A6 in Appendix A presents the initial environmental keyword that are used in our study.
[12] Rather, they are more related to the social dimension of the Environmental, Social, and Governance (ESG) Criteria. It somehow makes sense why *Word2vec* will regard these words as similar to environmental-related keywords because CEOs generally talk about ESG matters in the same contexts.
[13] Panel B of Table A6 in Appendix A presents the included and excluded keywords.

whether a firm uses CSR (ESG) contracting or not (see., e.g., Flammer, Hong, and Minor, 2019; Qin and Yang, 2022). However, unlike traditional financial statements (e.g., SEC Form 10K) that each section is itemized, the section titles of proxy statements are not either itemized or standardized, making it hard for researchers to use computer programs to automatically extract a standalone section from proxy statements.[14] Moreover, even if we can extract the Executive Compensation section from the whole proxy statement for each firm, there is still a limitation: the environmental words that are observed in Executive Compensation may not be in the context of discussing executive pays to environment, and may only act as an emphasis of corporate environmental consciousness. Thus, instead of focusing on a specific section, we rely on the whole textual content of proxy statements to construct the measure.

To ensure that environmental words are in the context of discussing executive pays to environment, we utilize a window approach, similar to Hassen et al. (2019), by requiring the environmental words be surrounded by compensation and executive related words. Specifically, we further construct two pre-specified keyword lists. The first list contains compensation related words: *compensation*, *pay*, *bonus*, *award*, *salary*, and *incentive*, while the second list contains executive related words: *executive*, *CEO*, and *NEO* (i.e., named executive officers).[15] We then determine a firm i has adopted environmental contracting in year t if there is at least one environmental related word e appeared in firm i's proxy statement in year t, and if there are also at least one compensation-related word and at least one executive related word appeared within 10 words before and after the environmental word e. The model is as follows:

$$ENV\_PAY_{it} = \mathbb{1}[e \in \mathbb{E}] \times \mathbb{1}[|e - c| < 10] \times \mathbb{1}[|e - m| < 10] \tag{1}$$

where $\mathbb{1}[\cdot]$ is an indicator function, $\mathbb{E}$ is the set of machine-learning-based environmental keywords, c is the position of the nearest compensation synonym, and m is the position of the nearest executive synonym. The *ENV_PAY* is in fact an indicator variable that determines whether a firm adopts environmental contracting in a specific year. It will equal one if we identify at least one machine-learning-based environmental word that occurs in proximity to

[14] For example, Section Item 1.A of a 10K filing is Risk Factors. Thus, we can easily extract the Risk Factors section by requiring the text to be within Item 1.A and Item 1.B. However, it is not the case in proxy statements. For example, in Apple Inc.'s 2021 DEF 14A filing, the Section Compensation Discussion and Analysis (CD&A) is not itemized followed by the Section Compensation Committee Report. While in Meta Platforms, Inc.'s 2021 DEF 14A filing, the CD&A is followed by the Section Perquisites and Other Benefits. Thus, to the best of our knowledge, we could not find a clean way to extract a standalone section from proxy statements. See, https://www.sec.gov/Archives/edgar/data/0000320193/000119312521001987/d767770ddef14a.htm and https://www.sec.gov/Archives/edgar/data/0001326801/000132680122000043/meta2022definitiveproxysta.htm.

[15] We do not use *Word2vec* to further expand the compensation and executive word lists because we believe the two lists of keywords can sufficiently capture words that are related to compensation and executive.

(within 10 words) the compensation and executive synonyms, and otherwise equal zero.[16] This measure ensures that the environmental words that we capture from the proxy statements of firms are used in the context of discussing executive compensation related issues and not the others, and also addresses the technical issue that the executive compensation section cannot be extracted alone from proxy statements. In addition to the indicator variable *ENV_PAY*, we also construct the other measure, *Log(1+ENV_PAY_COUNT)* by counting the number of occurrences of the environmental contracting in a proxy statement to capture a firm-year's mentioning intensity.

3.3. Control Variables

We control for a comprehensive list of time-varying firm-level characteristics that may be correlated with CEO compensation (see, for example, Core, Guay, and Larcker (2008); Graham, Li, and Qiu (2012); Correa and Lel (2016); Focke, Maug, and Niessen-Ruenzi (2017); Hoi, Wu, and Zhang (2019); Dai, Rau, Stouraitis, and Tan (2020)). In particular, we include the following firm-level control variables: *SIZE* which is the natural logarithm of total assets; *VOL* which is the standard deviation of the firm's daily stock returns in a year; *RET* which is the buy-and-hold return on the firm's stock over a year; *ROA* which is a ratio of operating income scaled by total assets; *MTB* which is a market-to-book ratio, where market equity is calculated by multiplying the closing share price by total shares outstanding and book equity is total common equity; *CASH* which is the ratio of cash balance to total assets; *LEV* which is the sum of current liabilities and long-term debt divided by total assets; *CAPX* which is the ratio of capital expenditures to total assets. The data to construct these firm-level control variables are sourced from Compustat and CRSP.

In addition, we account for CEO-level control factors: *CEO_AGE* which is the natural logarithm of one plus the CEO age; *CEO_TENURE* which is the natural logarithm of one plus the CEO tenure (i.e., the number of years since a CEO has been a CEO for the firm) (Focke, Maug, and Niessen-Ruenzi, 2017; Hoi, Wu, and Zhang, 2019; Dai, Rau, Stouraitis, and Tan, 2020). The data to construct these CEO-specific characteristics are sourced from ExecuComp.

With regard to the state-level control variables, we incorporate the following three measures to capture a state's economic conditions: *STATE_GDP* which is the natural logarithm of state income; *STATE_GDPGR* which is the growth rate in state income; *STATE_GDPCAP*

[16] For example, *ENV_PAY* will equal one for the sentence "Our *executive compensation* structure emphasizes on corporate *environmental* performance", and it will equal zero for the sentence "We care about corporate *environmental* performance".

which is the natural logarithm of per capita state income. The data to construct these variables are sourced from Bureau of Economic Analysis.

To mitigate the impact of outliers, we winsorize all continuous variables at their 1st and 99th percentiles. Table 1 provides the summary statistics of the variables used in the study. Detailed definitions of all variables can be found in Appendix Table A1.

[Insert Table 1 about here]

4. Empirical Results

4.1. Identification

We use a difference-in-differences (DiD) regression framework to examine the impacts of the SCAP finalization on investor attention to climate-related topics, firm perceived climate regulatory risk, CEO compensation, managerial pay-for-performance sensitivity (PPS) and risk-taking incentives, and firms' adoption of environmental contracting. Following Bertrand and Mullainathan (2003), we estimate the following model:

$$Y_{i,s,t+1} = \alpha + \beta\, SCAP_{s,t} + \gamma\, X_{i,s,t} + \pi_s + \omega_i + \tau_t + \varepsilon_{i,s,t,} \qquad (2)$$

Where:

i = firm i,

s = the firm's historical headquarter state, and

t = the current year.

Y is the dependent variable of interest in our study. *SCAP* is a dichotomous variable indicating whether the SCAP has been finalized in the firm's headquarter state s by year t, X is a vector of firms, CEO- and state-level control variables defined in Section 3 and measured in current year t, π_s is the headquarter state fixed effects, ω_i is the firm fixed effects, and τ_t is the year fixed effects. Including state fixed effects controls for unobservable conditions at the firm's headquarter state, which do not vary over time (e.g., geographical advantages) and may determine the dependent variables such as *TOTAL_PAY*. Including firm fixed effects controls for time-invariant firm characteristics that may affect our dependent variables of interest and thus estimates the treatment effect (i.e., SCAP implementation) within firm over time. Including year fixed effects helps account for the economy-wide shocks.[17]

An important advantage of the DiD setting is that different states finalized the SCAP at different points in time, which allows a given adopting state to be both a treatment and a control state. In addition, the specification is not affected by the fact that some states did not adopt the

[17] The baseline results remain qualitatively unchanged when we control for alternative sets of fixed effects, e.g., removing state fixed effects or replacing firm fixed effects with industry fixed effects.

SCAPs during our sample period and some states adopted the SCAPs after the end of our sample period. To address concerns about autocorrelation, we cluster standard errors at the headquarter state level given that the key independent variable of interest, *SCAP*, is a headquarter state-specific variable.

4.2. Whether SCAPs Affect Investor Attention to Climate-related Topics and Perceived Climate Regulatory Risk

First, we examine whether the finalization of the SCAP in a state will increase the attention of the market investors to climate-related topics, and local firms' perceived climate regulatory risks. We conjecture that the finalization of SCAPs will signal the markets that the state governments are determined to take climate-related actions (e.g., enact more environmental regulations and increase environmental monitoring) to combat climate change in the coming future, which will increase local market attention on climate-related topics and perceived climate regulatory risks faced by the local firms. The results are reported in Table 2.

[Insert Table 2 about here]

Panel A of Table 2 presents the results of the effect of SCAP finalization on investor attention to climate-related topics, which is measured by the Google Search Volume Index (SVI) on the keyword *climate*. We construct two dependent variables, *GSVI_CLIMATE* (Column 1 and 2) which is the level of Google SVI on *climate*, and *ΔGSVI_CLIMATE* (Column 3 and 4) which is the change in Google SVI on *climate*. We include state fixed effects and year fixed effects in all columns, and state controls in column 2 and 4 as well. The results show that the coefficients of the DiD indicator, *SCAP*, is positive and statistically significant at least at 10% level across all specifications. The economic magnitude is also considerable: compared with the non-SCAP-adopting states, the SCAP-adoption states on average increase the Google SVI on *climate* by 16 points and the change in Google SVI on *climate* by 10 points after the finalization of SCAPs.[18] The results suggest that the finalization of SCAPs significantly increases local markets' attention to climate-related topics.

[18] Note that Google SVI data on *climate* is normalized to be range 0 to 100. Specifically, Google Trend first calculates the popularity of the topic *climate* by using the number of searches on *climate* of each state each year divided by the total number of searches for all topics of that state in the same year. If not scale by the total searches, large states should have larger searching value for every topic which is not a good topic popularity measure. Next, the state with highest popularity of the topic *climate* in a year will be given the index value 100. The index value of the topic *climate* in other states will depend on their popularities relative to the state with the highest one. For example, the value of topic popularity in *climate* in California is 0.2, which is the highest among the states. Then its index value will equal 100. The value of topic popularity in *climate* in New York is 0.1, then its index value will equal 0.1/0.2 multiply by 100 which equals 50.
See https://support.google.com/trends/answer/4365533?hl=en&ref_topic=6248052

We further examine whether the SCAP finalization will increase a firm's perceived climate regulatory risk. The regression results are presented in Panel B of Table 2. We present the DiD results in a progressive manner. In particular, Column 1 includes only SCAP dummy without time-varying controls and with state and year fixed effects. Column 2 adds firm-level controls as well as firm fixed effects. Columns 2-3 further add CEO-level and state-level controls, respectively. It clearly shows that the coefficients of the DiD indicator, *SCAP*, are positive and statistically significant at 5% level across all specifications, consistent with our expectation that the finalization of SCAPs increases the perceived climate regulatory risk of firms that are headquartered in the SCAP-adopting states. In terms of the economic magnitude, the treated firms, on average, increase their perceived climate regulatory risk by 0.004 (account for about 12% of the sample mean; the sample mean of *ENV_RISK* is 0.0347) relative to the control firms after the passage of SCAP.

Taken together, the findings suggest that the finalization of SCAP in a state clearly signals to the local market investors and firms that the state government will take climate-related actions in the coming future, which significantly increase the attention to climate-related topics for local market investors and also increase the perceived climate regulatory risks for firms that are headquartered in the SCAP-adopting states.

4.3. The Impact of SCAP Adoption on CEO Total Compensation

Next, we investigate the effect of SCAP adoption in a state on executive compensation of the local firms. As we document an increase in treated firms' perceived climate regulatory risks, we conjecture that the shareholders of treated firms may lower these firms' executive pay to share the perceived future environmental compliance costs with corporate executives.

[Insert Table 3 about here]

Table 3 presents the estimation results of Equation 2. We present the DiD results in a progressive manner. In particular, Column 1 includes only SCAP dummy without time-varying controls and with state and year fixed effects. Column 2 adds firm-level controls as well as firm fixed effects. Columns 3-4 further add CEO-level and state-level controls, respectively. Across all models, the coefficients on the main variable of interest, *SCAP*, are negative and statistically significant. These results indicate a negative impact of the SCAP finalization on CEO total pay for the treated firms relative to control firms. The magnitude of the treatment effect is also economically meaningful. For example, the estimated coefficient of *SCAP* in Column 4 is -0.052 meaning that that the SCAP finalization in a state on average results in a reduction of total CEO pay by about 5.2% for treatment firms headquartered in that state relative to control firms headquartered in other states.[19]

To summarize, the baseline results in Table 3 lend support for Hypothesis 1 that the increase in perceived climate regulatory risks through the SCAP finalization leads local firms' shareholders to expect higher future compliance costs for the firms and hence shareholders lower the current executive pay of these firms to share the increased expected costs with corporate executives.[20]

4.4. Identification Validation

4.4.1. Parallel-trends assumption: Dynamic DiD

A causal interpretation of the effect of the SCAP implementation on CEO compensation in our DiD regressions requires that the CEO compensation by the treated and control firms follow parallel trends absent the changes in the status of the SCAP implementation. To identify the exact timing of the treatment effect, we employ a dynamic DiD regression framework. We first create a new set of adoption indicator variables: *SCAP_L1, SCAP_C0, SCAP_F1, SCAP_F2plus*, which are equal to one if the firm is headquartered in a state that will finalize the SCAPs in one year, finalizes the SCAPs in the current year, finalized the SCAPs one year ago, finalized the SCAPs two or more years ago, respectively, and zero otherwise.

We replace the *SCAP* indicator variable in the main tests with this new list of adoption indicator variables in the baseline model. Across all three columns in Table 4, we find that the coefficients of *SCAP_L1* and *SCAP_C0* are relatively smaller in magnitude and statistically insignificant. Meanwhile the coefficients of *SCAP_F1* and *SCAP_F2plus* are negative and statistically significant at 5% level throughout. These results show the treatment effect of SCAP finalization on CEO pay only exists from the treatment year onward but does not exist in any of the years prior to the treatment. More specifically, the negative treatment effect of the SCAPs

[19] This treatment effect is in general comparable to the impacts of other factors on CEO total pay. For example, Morse, Nanda, and Seru (2011) document an average 4.5% increase in CEO total pay for a one-standard-deviation increase in CEO power index (i.e., CEO personal influence over the board of directors); Hoi, Wu, and Zhang (2019) find an average 5.17% reduction in CEO total compensation for a one-standard-deviation increase in social capital (i.e., secular norms and social networks surrounding corporate headquarters). Looking at the impact of general corporate social responsibility (CSR), Cai, Jo, and Pan (2011) find a 4.35% (2.76%) decrease in CEO total compensation for an interquartile increase in CSR composite index (Net CSR) using KLD data.

[20] One may concern that the effect of SCAPs on CEO compensation may be driven by the differences in ex-ante firm characteristics and unobserved state-level economic variety. To address these concerns, we use propensity score matching (PSM) technique to select, for each treated firm, a control firm that has closest propensity score based on the firm characteristics measured one year before the SCAP adoption. In the second test, we further require the closest control firm to be headquartered in the neighbouring state to the treated firms' headquartered state. The results are reported in Table A3 and we find that the results are both qualitatively similar to our baseline results.

on CEO pay mainly shows up from one year after the policy changes. Hence, this finding suggests that the parallel-trend assumption for the efficacy of our DiD approach is satisfied and the documented effect is likely causal.

[Insert Table 4 about here]

4.4.2. Stacked-cohort Difference-in-Differences (DiD) Estimation

There may be several concerns in our empirical setting using the traditional difference-in-differences regression framework (see, Bertrand and Mullainathan, 2003). First, the pre- and post-treatment periods are unbalance: firms that are treated in earlier sample periods will have very short pre-treatment years, and firms that are treated in later sample periods will have very short post-treatment years. Second, the staggered adoption of SCAPs will result in that the early treated firms are used as control for later treated firms, which leads to potential underestimation of the treatment effect (Baker, Larcker, and Wang, 2022). Third, there can be a concern that the adoption of SCAPs is not fully exogenous because some unobserved time-varying local economic conditions may be correlated with both the propensity for a state to finalize the SCAP and the reduction in executive compensation.

To address the above concerns, we follow Gormley and Matsa (2011) to employ a stacked-cohort difference-in-differences regression framework. Specifically, for each treated state *s*, we form a cohort *c*. We then identify firms that are headquartered in state *s* as treated firms. We then match the treated firms in each SCAP-adoption event with control firms whose headquartered states never adopt SCAP but are neighboured to the SCAP-adoption state *s* to form a cohort *c*. We then stack the cohorts together to finalize the stacked-cohort DiD sample. Using this approach, we compare the changes in CEO compensation (*TOTAL_PAY*) between treated and control firms 10 years before and after each SCAP adoption event.

[Insert Table 5 about here]

The results are reported in Table 5. Similar to the baseline results, we continue to see a significant and negative reduction in CEO compensation of treated firms. The economic magnitude is also comparable: on average, the treated firms reduce their CEO compensation by about 5.5% relative to the control firms after the SCAPs, where the negative effect is 5.2% in the baseline regressions. To validate that the treatment effects of the SCAP adoption on CEO compensation from the stacked-cohort DiD regressions are not driven by nonparallel trends, we follow the approach proposed by Gormley and Matsa (2016) to construct a modified version of Equation 2, where we allow the effect of SCAP adoption on executive pay to vary by year. The visualized treatment effect is illustrated in Figure 1. It shows that before or in the years of

SCAP adoption, the coefficients are flatted around zero, suggesting no differences existed on the CEO compensation level between the treated and control firms. However, after the SCAP adoption year, the executive pay of the treated firms is sharply decreased relative to the control firms. The figure again confirms that the parallel-trends assumption underlying the stacked-cohort DiD estimation is satisfied.

Overall, the results suggest the robustness of the documented treatment effect of SCAPs on CEO compensation. We continue to see a significant decrease in executive pay of the treated firms after SCAP adoption. Moreover, the parallel-trend figure explicitly visualizes that there is no indication of a decrease in CEO compensation before the SCAP; the negative effect is only observed from one year after the adoption of SCAP, supporting that the documented effect is likely causal.

[Insert Figure 1 about here]

4.5. Heterogenous Treatment Effect

4.5.1. The Role of SCAP Uncertainty

If the SCAP indeed reduces CEO pay through amplifying climate regulatory risk, then it is intuitive that the economic impact of the SCAP increases as climate regulatory risk heightens. Here, we argue any new environmental policy comes with a certain level of uncertainty as to which goals/objectives the policy is aimed at achieving. The less goals and objectives being specified and communicated with the corporate world, the more uncertainty the local firms are about the policy implementation and hence the greater the regulatory risks facing these firms. That is, local firms in a state with less detailed goals/objectives in its SCAP may only know that the state is determined to take climate-related actions but may not know in detail what actions (including legislative actions) the state will take, which can further increase the perceived climate regulatory risks of local firms.

We first verify whether it is indeed the case; that is, firms will experience higher climate regulatory risks if they are headquartered in states with less detailed goals in SCAP. Specifically, we follow Ray and Grannis (2015) and count the number of specific goals for each state's SCAP policy either in total or for each of the 3 subcategories (planning and capacity building, law and policy, and post-implementation monitoring). We then construct a dummy variable *SCAP_UNCERTAIN_HIGH* indicating below median number of goals in year *t*. Exploiting a triple-difference-in-differences regression framework with same sets of control variables and fixed-effect specifications as in Equation 1, we interact the DiD indicator (*SCAP*) with *SCAP_UNCERTAIN_HIGH* and regress the perceived climate regulatory risks (*ENV_RISK)* on the interaction term. The results are presented in Panel A of Table 6.

[Insert Table 6 about here]

We find that the estimated coefficients of the interaction term are statistically significant and positive across three out of four regressions. It suggests that the effect of SCAP finalization on firms' perceived climate regulatory risk is more pronounced if the SCAP implementation process is relatively more uncertain with less specific goals (and hence, greater climate regulatory risk). The evidence is consistent with our expectation that the SCAP adoption will further increase the local firms' perceived climate regulatory risks if there are more uncertainties in the state's SCAP (less detailed goals/objectives), because the firms may not be able to anticipate the future environmental regulation intensity and the related compliance costs.

After documenting that the treated firms will have higher climate regulatory risks if they are headquartered in states with higher SCAP uncertainty, we next examine whether these firms will decrease more their CEO compensation when the environmental regulatory risks are perceived higher. We again employ the triple-DiD regression framework, but this time we regress firms' CEO compensation (*TOTAL_PAY*) on the interaction term of *SCAP* and *SCAP_UNCERTAIN_HIGH*. The results are reported in Panel B of Table 6.

Consistent with our expectation, we find that the coefficients of the interaction term are statistically significant and positive across all four regressions. This suggests that the dampening effect of SCAP finalization on CEO pay is even more pronounced if the SCAP implementation process is relatively more uncertain with less specific goals (greater climate regulatory risks). The results lend further support to the interpretation that the SCAP finalization reduces CEO pay through increasing their perceived climate regulatory risks.

Taken together, we investigate the role of SCAP uncertainty play on firms' perceived climate regulatory risks and CEO compensation. We find that the positive effects of SCAP adoption on perceived climate regulatory risks are stronger for the treated firms that are headquartered in states with higher SCAP uncertainty (less detailed goals/objectives in SCAPs). Moreover, due to the higher perceived climate regulatory risks, these treated firms will reduce more executive compensation as a way to share the increased environmental compliance costs with corporate executives.

4.5.2. The Role of Climate Risk

Next, we seek to provide further support for our theoretical argument that the increased climate regulatory risks through the SCAP finalization leads the shareholders of the treated firms to reduce executive pay to share the future compliance costs with corporate executives. To do so, we conduct cross-sectional tests to better understand the heterogeneities in the SCAP impact on CEO pay. We predict that if our conjecture holds true, then the negative effect of SCAP finalization on executive compensation should be stronger for (i) firms headquartered in states where market participants are more concerned about climate-related topics; ii) executives more perceive climate regulatory risk; iii) firms receive lower external environmental ratings, and iv) firms have more internal environmental concerns. These four categories of firms can be regarded as either externally or internally sensitive to climate regulatory risks.

To examine the role of investor attention to climate-related topics in the effect of SCAPs on CEO compensation, we construct an indicator variable, *GSVI_CLIMATE_HIGH*, that equals one if firms' headquartered states' Google search volume on the keyword *climate* is above median value in year *t* and otherwise equals zero. To classify firms with greater perceived climate regulatory risk, we construct an indicator variable, *ENV_RISK_HIGH*, that equals one if firms' political-and-environmental risk exposure as constructed by Hassan et al. (2019) is above median value in year *t* and otherwise equals zero. We first present the results in Panel A of Table 7. We find that the coefficients of the two interaction terms are both negative and statistically significant, indicating that the negative treatment effect of SCAP adoption on CEO compensation is in fact more pronounced for firms that are headquartered in states where investors care more about climate-related issues, and for firms that are perceiving higher climate regulatory risk.

[Insert Table 7 about here]

To examine whether a firm with lower external environmental ratings will lower their CEOs compensation more after the finalization of SCAPs, we further generate two indicator variables, *ENV_CONCERN_HIGH* which equals one if firms' environmental concerns from MSCI KLD is above median value in year *t* and otherwise equals zero, and *ENV_RATING_LOW* which equals one if firms' environmental ratings from Sustainalytics is below the median value in year *t* and otherwise equals zero. [21] We expect that a firm that has

[21] Note that we focus on environmental concerns (rather than environmental strengths) to precisely capture the firm's sensitivity to climate risks. For example, a firm with a poor waste processing system (environmental concern) is hardly offset by a good carbon emission control (environmental strength).

more (lower) external environmental concerns (external environmental ratings) should be subject to even higher future climate regulatory costs that are imposed by the adoption of SCAPs. The results of the cross-sectional tests are presented in Panel B of Table 7. Again, we find that the coefficients of the two interaction terms are both negative and statistically significant, which show that a firm that is evaluated as having more environmental concern and having lower environmental rating by external rating agencies will cut more CEO pay after the SCAP adoption. It is consistent to our hypothesis that shareholders of treated firms will cut their CEOs compensation with the purpose of sharing future climate regulatory risk, particularly for those firms that are having more environmental concerns and lower environmental ratings.

Finally, we examine the role of a firm's inherent environmental risk and thus construct two alternative indicators. First, *ENV_LAWSUIT* is a dummy indicating whether the firm is involved as a defendant in an environmental lawsuit that starts in year *t*, where data on environmental lawsuits is sourced from AuditAnalytics database. Second, *STRANDED_ASSET* is a dummy indicating GICS industry of Metals & Mining; Oil, Gas & Consumable Fuels; Electric Utilities; Gas Utilities; Chemicals; Construction Materials; Independent Power Producers & Energy Traders; or Energy Equipment & Services.[22] We then augment the baseline DiD model by interacting each of these climate risk sensitivity indicators with the *SCAP* indicator. The results of these cross-sectional tests in Panel C of Table 7 show negative and statistically significant coefficients on the interaction terms. This means the SCAP adoptions at headquarter states exert even more adverse influence on the CEO pay for firms that more prone to climate risks (i.e., those that experience environment lawsuits, or hold stranded assets when climate regulations become more stringent).

Taken together, the results support Hypothesis 2 that the negative effect of SCAP on CEO pay is more pronounced for firms with higher climate regulatory risk ex-ante: firms that are headquartered in states where investors pay more attention to climate-related issues; firms that have higher perceived climate regulatory risks, firms that have higher externally-evaluated environmental concerns and lower environmental ratings; firms that are facing higher

[22] Krueger, Sautner, and Starks (2020) document a list of top stranded asset risk, including (1) coal producers, (2) unconventional oil producers, (3) conventional oil producers, (4) natural gas producers, (5) iron and steel producers, and (6) conventional electricity producers. Similarly, Nguyen and Phan (2020) and Balachandran and Nguyen (2018) develop of list of highest GICS emitting industries, including (1) Oil, Gas & Consumable Fuels; (2) Electric Utilities; (3) Gas Utilities; (4) Independent Power Producers & Energy Traders; (5) Multi-Utilities; (6) Chemicals; (7) Construction Materials; (8) Metals & Mining; and (9) Paper & Forest Products.

environmental litigation risks, and firms that are holding more stranded assets in fossil-fuel-intensive industries.

4.5.3. The Role of CEO Power and Corporate Governance

Lastly, we shed light on the role of CEO power and firms' external threats in the effect of the SCAP finalization on CEO compensation. As we discussed before, the SCAP finalization will tend to increase the SCAP-adopting states' climate regulation intensity, motivating the shareholders of the treated firms to seek the risk sharing from their CEOs through lowering CEO compensation. However, if the CEOs of the treated firms have more negotiation power, the shareholders may not be able to easily lower the CEO compensation. Thus, we expect the negative effect of SCAP adoption on CEO compensation should be weaker for the treated firms where the negotiation power is more concentrated on the CEOs. We proxy for a CEO's negotiation power by using two indicator variables: *CEO_TENURE_LONG* which equals one if the CEO tenure of a firm in year *t* is longer than 10 years and otherwise equals zero, and *CEO_OWN_LARGE* which equals one if the CEO ownership of a firm is more than 5% in year *t* and otherwise equals zero. We then interact the two dummies with our DiD indicator, *SCAP*, to conduct cross-sectional analyses on CEO compensation between firms that have high-power CEOs and those with lower-power CEOs.

Similarly, firms' external threats from the product markets and the market for corporate control can also play an important moderating role. A firm that face greater external threats should be more sensitive to the perceived increase in future environmental compliance costs because of the SCAP finalization. Thus, to achieve better corporate risk control, those firms facing greater external threats should respond to the SCAP finalization more strongly, requiring their CEOs to be aligned with shareholder interests and thus cutting the CEO compensation more. We use different proxies to examine the moderating role of external threats in the effect of SCAP finalization on CEO compensation. First, we proxy for external threats from the product markets using product market competition.[23] We follow Hoberg and Phillips (2010; 2016) and use a text-based analysis of the firm's 10-K product descriptions to develop two measures of product market competition: (i) Herfindahl-Hirschman index, which is a concentration measure and calculated by using the traditional Herfindahl-Hirschmann sum of squared market shares formulation, with lower values indicating higher competition, and (ii)

[23] A large strand of literature suggests that firms in the industries with higher production market competition have greater risk in becoming unprofitable and being liquidated (see, e.g., Hart, 1983; Schmidt, 1997; Giroud and Mueller, 2011).

total similarity index, which is a total similarity measure and computed as the sum of pairwise similarities between the given firm and all other firms, with higher values indicating higher competition. We construct two dummy variables, *HHI_LOW* and *TSIM_HIGH*, which indicate relatively higher competition than the cross-sectional median values in year *t*.

Second, we proxy for a firm's external threats from the market for corporate control using the hostile takeover index developed in Cain, McKeon, and Solomon (2017), with higher values indicating higher likelihood that the firm is acquired in a hostile manner. We then construct a dummy variable, *HOSTILE_HIGH*, which indicates relatively higher hostile index than the cross-sectional median value in year *t*. All of the three indicators are then interacted with the DiD indicator, *SCAP*, to examine the heterogenous treatment effect.

The cross-sectional tests of the role of CEO power and external threats are presented in are presented in Panel A and B of Table 8, respectively. Consistent to our expectation, in Panel A, the coefficients of the two interaction terms with CEO power are both positive and statistically significant, indicating that the effect of SCAP on CEO compensation is weaker for firms whose CEOs have more negotiation power. In fact, the results show that the treated firms whose CEOs are powerful do not decrease their CEO pay: in column 1 (column 2), the coefficients of *SCAP* and the interaction term is -0.073 (-0.061) and 0.072 (0.088) respectively. In panel B, we can see that the coefficients of the three interaction terms with corporate governance are all negative and statistically significant, which suggests that those treated firms facing greater external threats form the product markets or the market for corporate control, cut their CEO pay more in response to the SCAP finalization.

Taken together, the results show that CEO negotiation power and firms' external threats are two important moderating factors that help explain the heterogenous effects of the SCAP finalization on CEO compensation. We find that treated firms whose CEOs have greater negotiation power do not decrease their CEO pay relative to the control firms after the SCAP finalization. By contrast, those treated firms facing greater external threats, as proxied by greater product market competition and/or greater hostile takeover likelihood, decrease their CEO compensation more after the SCAP finalization.

5. Additional Analyses

5.1. The SCAP Adoption and Managerial PPS and Risk-Taking Incentives

In this section, we provide additional tests for our conjecture that shareholders become risk averse when facing with heightened climate regulatory risks. In particular, we argue that if managerial profit-seeking and risk-taking activities may expose the treated firms to more climate regulatory risks and higher compliance costs following the SCAP adoption, then shareholders may reduce these incentives.[24]

To measure CEO risk-taking incentives, we follow Coles, Daniel, and Naveen (2006) and construct CEO pay-performance sensitivity (*DELTA*) and CEO wealth-stock-volatility sensitivity (*VEGA*), with higher values indicating greater incentives. We then run DiD regressions of each of these CEO incentive metrics on the *SCAP* dummy variable with all controls as per the baseline model. The results in Table 9 show negative and statistically significant coefficients on the *SCAP* indicator for both *DELTA* and *VEGA*. This means CEO pay becomes less dependent on the firm's financial performance, and CEO wealth in general becomes less sensitive the firm's stock volatility post-SCAP. In other words, shareholders react to the SCAP finalization at the firm's headquartered state by reducing executive risk-taking incentives. The evidence provides further support for the shareholder risk aversion hypothesis.

[Insert Table 9 about here]

5.2. The SCAP Adoption and Environmental Contracting

Next, we investigate whether treated firms are more likely to use environmental contracting, that is, linking CEO compensation to corporate environmental performance. We conjecture that after the SCAP adoption in a state, the treated firms will tend to orient executive pay towards future corporate environmental performance in an effort to decrease expected future compliance costs. From this point of view, we shed light on a firm's adoption of environmental contracting.

Unlike the traditional executive compensation structure that links executive pays to financial performance that is relatively short-termism, the environmental contracting, or broadly speaking, the CSR (ESG) contracting, is established by firms to raise CEOs attention more to corporate environmental and social performance that are arguably more long-termism. As climate change issues become more severe, firms start to utilize CSR contracting.

[24] In complementary analyses, we investigate the effect of SCAPs on the components of executive compensations. If shareholders of the treated firms expect the effect of the SCAP finalization to be only short-term, then they may just reduce cash-based CEO pay such as salaries and bonuses. On the other hand, if they deem the SCAP impact to be long-term, then they may also decrease equity-based CEO pay such as restricted stock, options granted, as well as long-term incentive payouts. The results are reported in Table A4 in the appendix. It shows that SCAP leads to a decrease in both the cash and equity component of executive compensation, while equity component decreases more (12.1% versus 6.6%). It indicates that shareholders of the treated firms expect the increased climate regulatory risks induced by the SCAP finalization to have both short-term and long-term impacts. Moreover, we examine whether the negative effect is also observed in the top5 non-CEO-executive compensation and we find that it is the case. The results presented in Table A5 in the appendix suggest that the adoption of SCAPs leads to a 6.4% decrease in the total compensation of top5 non-CEO-executive staffs, suggesting that the effect is not limited to just CEOs.

According to Flammer, Hong, and Minor (2019), about 12% of S&P 500 firms adopt CSR contracting in 2004, and it increases to 37% in 2013. Prior studies also examine the effect of CSR contracting on corporate policy responses. For example, Flammer, Hong, and Minor (2019) find that firms that adopt CSR contracting will have higher firm value and CSR scores, lower emissions, and generate more green patents. Similarly, Cohen et al. (2022) document a positive relationship between ESG contracting adoption and future ESG performance, and the improved ESG performance also leads to higher executive compensation. Overall, it suggests that adopting CSR contracting indeed helps to direct CEO attention from short-term financial performance to long-term sustainable performance.

We thus expect that although the shareholders of the treated firms reduced CEOs incentives in profit-chasing and risk-seeking activities, they should be more likely to substitute such financial incentives for environmental metrics, which will lead the treated firms to adopt environmental contracting, i.e., linking their CEOs compensation to future environmental performance. To test this conjecture, we construct an indicator variable, *ENV_PAY*, that equals one if firms' proxy statements contain one of our machine-learning-based environmental keywords, and if that environmental keyword is surrounded by a compensation-related keyword and an executive-related keyword, otherwise equals zero. We impose stringent criteria that requires the environmental-related keyword to be neighboured with compensation and executive related words because in that way we ensure that the environmental keyword is in fact in the context of discussing about executive compensation, which lowers the concerns about false positives. Moreover, we also construct another variable, *Log(1+ENV_PAY_COUNT)*, to capture a firm's mentioning intensity of environmental contracting.

[Insert Table 10 about here]

We then employ the difference-in-differences regression in Equation 2 to examine whether the treated firms are more likely to adopt and mention more about environmental contracting. The results are reported in Table 10. Column 1-2 show the results of the likelihood of adopting the environmental contracting, and column 3-4 present the results of the mentioning intensity of the environmental contracting in proxy statements. We can see that the coefficients of *SCAP* are all positive and statistically significant at 1% level across all specifications. The results are robust to using either Probit model or OLS model to examine the likelihood of environmental contracting adoption, and are robust to using either Tobit or OLS model to examine the mentioning intensity of environmental contracting. Moreover, the economic magnitude is sizable: after the SCAP finalization, the treated firms, on average, are

7.6% more likely than the control firms to link CEO pays to environment, and they mention the environmental contracting by 8.3% more than the control firms in the proxy statements.

Overall, the results confirm our hypothesis that the treated firms will be more likely to link CEO pays to corporate environmental performance, directing CEOs attention to more on improving firms' environmental records and less on simply chasing for short-term financial performance.

5. Conclusion

Different state governments in the U.S. have begun to adopt plans, policies and regulations to prepare for and combat the significant threats of climate changes. The finalization of these climate action plans, policies and regulations in a state results in an adaptation plan—the SCAP. As the action plans, policies and regulations embedded in the SCAP of a state are binding on all firms located in that state, the SCAP finalization in a state is an increase of climate regulatory risks on firms in that state. Employing a difference-in-differences (DiD) regression framework, we find that the SCAP finalization in a state on average leads the local market in that state to pay more attention to climate-related topics. Also, it leads the firms headquartered in that state to have higher perceived climate regulatory risk, validating our hypothesis that the adoptions of SCAPs do increase the associated states' climate regulatory risks. Further analyses show a reduction of total CEO pay by about 5% for treatment firms headquartered in the SCAP-adopting state relative to control firms headquartered in non-adopting states. The negative treatment effect also holds for non-executive compensation.

The heterogenous treatment effect tests show that the negative effects of the SCAP finalization on CEO compensation is more pronounced for treated firms in states with more uncertain SCAP plans because of the higher future climate regulatory risks. Further, the negative effect on CEO compensation is also found to be more pronounced for firms in states where investor care more about climate-related topics, for firms with higher perceived climate regulatory risk, for firms that have more (lower) external-evaluated environmental concerns (ratings), and for firms that are inherently more sensitive to climate risk—firms facing greater environmental litigation risks or holding more stranded assets. Interestingly, we find that the negative effect is offset if CEO negotiation power of treated firms is stronger, but is more pronounced if corporate governance of treated firms is better.

Additional analyses reveal that both the cash-based and equity-based components of CEO pay decrease after the SCAP finalization, indicating that the shareholders deem SCAP-induced materialization in climate regulatory risks to have both short-term and long-term impacts on treated firms. Moreover, shareholders of treated firms reduce their CEOs profit-chasing and risk-taking incentives, probably because these activities will likely incur more future environmental compliance costs. Instead, the CEO pay is more likely to be linked to corporate environmental performance; that is, the treated firms adopt environmental contracting to shift CEOs incentives from targeting on short term financial performance to focusing on long term environmental records. Our findings may be of interest to academics, investors, and environmental policymakers.

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Figure 1. CEO Compensation around the SCAP Adoptions

This figure plots the point estimates from a stacked-cohort difference-in-differences specification that examines the effect of SCAP adoption on CEO compensation. The specification is a modified version of Equation 2 where we allow the effect of SCAP adoption to vary every year within the event window.

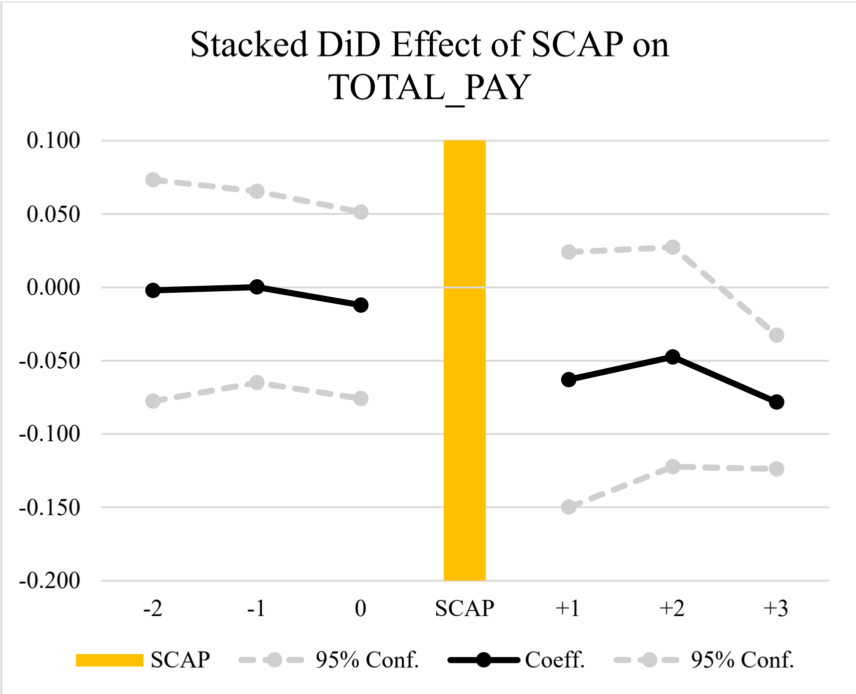

Table 1. Summary Statistics

The sample consists of 25,267 firm-year observations over the period 1994-2018. A detailed description of the variable construction is provided in the Appendix Table A1. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Obs.	Mean	Std. Dev.	25th Percentile	50th Percentile	75th Percentile
Panel A: Key Dependent Variables						
$TOTAL\_PAY_{t+1}$	25,267	8.046	1.076	7.351	8.109	8.796
$CASH\_PAY_{t+1}$	25,267	6.738	0.881	6.399	6.776	7.099
$EQUITY\_PAY_{t+1}$	25,267	2.073	3.356	0.000	0.000	5.701
$CASH\_PAY\_RATIO_{t+1}$	25,182	0.369	0.272	0.156	0.279	0.520
$DELTA_{t+1}$	23,522	4.435	1.376	3.492	4.404	5.355
$VEGA_{t+1}$	23,518	2.874	1.576	1.853	3.004	4.020
Panel B: Key Independent Variable						
$SCAP_t$	25,267	0.210	0.407	0.000	0.000	0.000
Panel C: Firm-level Control Variables						
$SIZE_t$	25,267	7.555	1.711	6.304	7.429	8.648
VOL_t	25,267	-3.956	0.556	-4.349	-4.008	-3.609
RET_t	25,267	0.019	0.106	-0.037	0.015	0.068
ROA_t	25,267	0.040	0.129	0.014	0.047	0.086
MTB_t	25,267	3.196	5.928	1.446	2.247	3.773
$CASH_t$	25,267	0.156	0.177	0.028	0.087	0.224
LEV_t	25,267	0.220	0.207	0.050	0.197	0.332
$CAPX_t$	25,267	0.049	0.051	0.016	0.034	0.064
Panel D: CEO-level Control Variables						
CEO_AGE_t	25,267	4.034	0.127	3.951	4.043	4.127
CEO_TENURE_t	25,267	1.792	0.875	1.099	1.792	2.398
Panel E: State-level Control Variables						
$STATE\_GDP_t$	25,267	12.942	0.929	12.331	12.938	13.691
$STATE\_GDPGR_t$	25,267	0.045	0.028	0.030	0.047	0.064
$STATE\_GDPCAP_t$	25,267	10.568	0.258	10.401	10.589	10.749

Table 2. The Effect of SCAP Adoption on Investor Attention to Climate-related Topics and Perceived Climate Regulatory Risk

This table reports the results of the difference-in-differences regressions of investor attention to climate-related topics, and perceived climate regulatory risk on *SCAP* indicator. In Panel A, we capture investor awareness on climate-related topics using the Google search volume index (GSVI) on the keyword *climate* by each state-year. We include state fixed effects as well as year fixed effects in all specifications. State-level controls are also included in column 2 and 4. In Panel B, we capture investors' perceived climate regulatory risk using firm-level exposure in political risk on environmental topics generated by Hassen et al. (2019). Most specifications include state fixed effects, firm fixed effects, and year fixed effects. Column 1 is estimated without any control; column 2 controls for firm-level characteristics; column 3 controls for both firm-level and CEO-level characteristics; column 4 controls for firm-level, CEO-level, and state-level characteristics, respectively. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Google Search Volume on "climate"

	(1)	(2)	(3)	(4)
VARIABLES	$GSVI\_CLIMATE_{t+1}$		$\Delta GSVI\_CLIMATE_{t+1}$	
SCAP	**18.776***	**15.831***	**10.612****	**10.328****
	(9.631)	(8.968)	(4.838)	(4.639)
STATE_GDP		27.298		24.074
		(90.600)		(20.298)
STATE_GDPGR		54.239		-104.560
		(103.523)		(80.867)
STATE_GDPCAP		-141.624		-52.747*
		(105.982)		(26.427)
State FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs.	765	765	765	765
Adj. R^2	0.793	0.795	0.536	0.537

Panel B. Perceived Climate Regulatory Risk by Hassen et al. (2019)

VARIABLES	(1)	(2)	(3)	(4)
		ENV_RISK $_{t+1}$		
SCAP	**0.004****	**0.004****	**0.004****	**0.004****
	(0.002)	(0.001)	(0.001)	(0.001)
SIZE		0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)
VOL		0.001*	0.001*	0.001*
		(0.001)	(0.001)	(0.001)
RET		0.004*	0.004*	0.004*
		(0.002)	(0.002)	(0.002)
ROA		-0.001	-0.001	-0.001
		(0.002)	(0.002)	(0.002)
MTB		-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)
CASH		0.007	0.007	0.007
		(0.004)	(0.004)	(0.004)
LEV		-0.003	-0.003	-0.003
		(0.003)	(0.003)	(0.003)
CAPX		-0.005	-0.005	-0.005
		(0.009)	(0.009)	(0.009)
CEO_AGE			0.000	0.000
			(0.005)	(0.005)
CEO_TENURE			0.000	0.000
			(0.001)	(0.001)
STATE_GDP				-0.008
				(0.017)
STATE_GDPGR				-0.010
				(0.021)
STATE_GDPCAP				0.018
				(0.024)
State FEs	Y	Y	Y	Y
Firm FEs	N	Y	Y	Y
Year FEs	Y	Y	Y	Y
Obs.	18,828	18,828	18,828	18,828
Adj. R^2	0.036	0.474	0.474	0.474

Table 3. The Effect of SCAP Adoption on CEO Compensation

This table reports the results of the difference-in-differences regressions of CEO compensation (*TOTAL_PAY*) on *SCAP* indicator. While column 1 includes only state and year fixed effects with no controls, all the other specifications include state fixed effects, firm fixed effects, and year fixed effects. Column 2 further controls for firm-level characteristics; column 3 controls both firm-level and CEO-level characteristics; column 4 controls firm-level, CEO-level, and state-level characteristics, respectively. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES		$TOTAL\_PAY_{t+1}$		
SCAP	**-0.095****	**-0.054*****	**-0.050****	**-0.052*****
	(0.038)	(0.019)	(0.019)	(0.019)
SIZE		0.233***	0.232***	0.231***
		(0.019)	(0.019)	(0.020)
VOL		-0.041**	-0.041**	-0.041**
		(0.017)	(0.017)	(0.017)
RET		0.213***	0.210***	0.209***
		(0.041)	(0.041)	(0.042)
ROA		0.340***	0.332***	0.328***
		(0.081)	(0.080)	(0.081)
MTB		0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)
CASH		0.026	0.028	0.029
		(0.086)	(0.089)	(0.088)
LEV		-0.283***	-0.282***	-0.283***
		(0.065)	(0.064)	(0.063)
CAPX		0.327	0.291	0.289
		(0.203)	(0.200)	(0.199)
CEO_AGE			-0.245***	-0.248***
			(0.070)	(0.071)
CEO_TENURE			0.045***	0.045***
			(0.009)	(0.009)
STATE_GDP				0.141
				(0.184)
STATE_GDPGR				0.753
				(0.489)
STATE_GDPCAP				-0.393
				(0.267)
State FEs	Y	Y	Y	Y
Firm FEs	N	Y	Y	Y
Year FEs	Y	Y	Y	Y
Obs.	25,267	25,267	25,267	25,267
Adj. R^2	0.094	0.682	0.683	0.683

Table 4. Parallel Trends Assumption Check: Dynamics of SCAP Adoption Effect

The table reports results of the falsification test that counterfactually assumes that the SCAP finalization takes place a few years before and after the actual event. The dependent variable is CEO compensation (*TOTAL_PAY*) measured in year *t*. *SCAP_L1, SCAP_C0, SCAP_F1,* and *SCAP_F2plus* are indicator variables that indicate one year before, the current year of, one year after, and two or more years after the actual SCAP finalization, respectively. All regressions control for firm-level characteristics, while column 2 controls for both firm-level and CEO-level characteristics, and column 3 controls for firm-level, CEO-level, and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
VARIABLES		*TOTAL_PAY $_t$*	
SCAP_L1	**-0.044**	**-0.043**	**-0.033**
	(0.029)	(0.029)	(0.028)
SCAP_C0	**-0.058**	**-0.054**	**-0.047**
	(0.031)	(0.031)	(0.032)
SCAP_F1	**-0.085****	**-0.082****	**-0.082****
	(0.034)	(0.034)	(0.036)
SCAP_F2plus	**-0.066****	**-0.062****	**-0.065****
	(0.028)	(0.029)	(0.028)
Firm Controls	Y	Y	Y
CEO Controls	N	Y	Y
State Controls	N	N	Y
State FEs	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Obs.	25,267	25,267	25,267
Adj. R^2	0.679	0.679	0.679

Table 5. Stacked-cohort Difference-in-Differences Estimation

This table presents the results of stacked-cohort Difference-in-Differences (DiD) regressions that compares the changes in CEO compensation (*TOTAL_PAY*) between firms that are headquartered in treated (SCAP-adoption) states and firms that are headquartered in neighbouring-and-control states. Specifically, for each treated state *s*, we form a cohort *c* as follows: We identify firms that are headquartered in state *s* as treated firms. We then match the treated firms with control firms whose headquartered states are never treated (never adopt SCAP) but are neighbouring states of the treated state *s* to form the cohort. After forming all the cohorts for treated states, we stack the cohorts of treated and control firms together to finalize stacked-cohort DiD sample. We compare the changes in CEO compensation (*TOTAL_PAY*) between treated and control firms 10 years before and after each SCAP adoption event. All regressions control for firm-level characteristics, while column 2 controls for both firm-level and CEO-level characteristics, and column 3 controls for firm-level, CEO-level, and state-level characteristics. All specifications include state-cohort fixed effects, firm-cohort fixed effects, and year-cohort fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
VARIABLES		$TOTAL\_PAY_{t+1}$	
SCAP	**-0.048****	**-0.045****	**-0.055****
	(0.022)	(0.022)	(0.027)
Firm Controls	Y	Y	Y
CEO Controls	N	Y	Y
State Controls	N	N	Y
State-cohort FEs	Y	Y	Y
Firm-cohort FEs	Y	Y	Y
Year-cohort FEs	Y	Y	Y
Obs.	17,723	17,723	17,723
Adj. R^2	0.689	0.689	0.689

Table 6. Heterogenous Effect: The Role of SCAP Uncertainty

This table reports the role of SCAP uncertainty plays on the firms' perceived climate regulatory risks (*Panel A*) and CEO compensation (*Panel B*). *SCAP_UNCERTAIN_HIGH* is a dummy indicating below median SCAP goals. All regressions control for firm-level, CEO-level, and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. The Role of SCAP Uncertainty on Firm-Level Perceived Climate Regulatory Risks

	(1)	(2)	(3)	(4)
VARIABLES		*ENV_RISK* $_{t+1}$		
SCAP Goals	All	Planning	Law	Monitoring
SCAP*SCAP_UNCERTAIN_HIGH	**0.003***	**0.004****	**0.002**	**0.005*****
	(0.002)	(0.002)	(0.002)	(0.001)
SCAP	0.003**	0.002	0.003**	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
Firm Controls	Y	Y	Y	Y
CEO Controls	Y	Y	Y	Y
State Controls	Y	Y	Y	Y
State FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Observations	18,608	18,608	18,608	18,608
Adj. R^2	0.322	0.322	0.322	0.322

Panel B. The Role of SCAP Uncertainty on CEO Compensation.

	(1)	(2)	(3)	(4)
VARIABLES		*TOTAL_PAY* $_{t+1}$		
SCAP Goals	All	Planning	Law	Monitoring
SCAP*SCAP_UNCERTAIN_HIGH	**-0.057****	**-0.061****	**-0.052***	**-0.052*****
	(0.024)	(0.025)	(0.028)	(0.019)
SCAP	-0.020	-0.017	-0.021	0.000
	(0.027)	(0.029)	(0.029)	(0.000)
Firm Controls	Y	Y	Y	Y
CEO Controls	Y	Y	Y	Y
State Controls	Y	Y	Y	Y
State FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Obs.	25,267	25,267	25,267	25,267
Adj. R^2	0.683	0.683	0.683	0.683

Table 7. Heterogenous Effect: The Role of Climate Risk

This table reports the results of the difference-in-differences regressions of CEO compensation (*TOTAL_PAY*) on *SCAP* indicator, conditional on different proxies of climate risk. In Panel A, we examine the role of investor attention to climate risk. *GSVI_CLIMATE_HIGH* is a dummy variable that equals one if firms' headquartered states' Google search volume on the keyword *climate* is above median value in year *t* and otherwise equals zero; *ENV_RISK_HIGH* is a dummy variable that equals one if firms' environmental risk exposure measured by Hassan et al. (2019) is above median value in year *t* and otherwise equals zero. In Panel B, we examine the role of external environmental ratings. *ENV_CONCERN_HIGH* is a dummy variable that equals one if firms' environmental concerns from MSCI KLD is above median value in year *t* and otherwise equals zero; *ENV_RATING_LOW* is a dummy variable that equals one if firms' environmental ratings from Sustainalytics is below the median value in year *t* and otherwise equals zero. In Panel C, we examine the role of internal environmental concerns. *ENV_LAWSUIT* is a dummy variable that equals one if the firm is involved as a defendant in an environmental lawsuit that starts in year *t* and otherwise equals zero; *STRANDED_ASSET* is a dummy variable that equals one if firms are in the following GICS industries: Metals & Mining; Oil, Gas & Consumable Fuels; Electric Utilities; Gas Utilities; Chemicals; Construction Materials; Independent Power and Renewable Electricity Producers; or Energy Equipment & Services, and otherwise equals zero. All regressions control for firm-level, CEO-level, and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Investor Attention to Climate Risk

	(1)	(2)
VARIABLES	*TOTAL_PAY* $_{t+1}$	
SCAP*GSVI_CLIMATE_HIGH	**-0.082***	
	(0.043)	
SCAP*ENV_RISK_HIGH		**-0.046***
		(0.024)
SCAP	0.054***	0.020
	(0.018)	(0.027)
GG_CLIMATE_HIGH	0.018	
	(0.015)	
ENV_RISK_HIGH		0.008
		(0.010)
Firm Controls	Y	Y
CEO Controls	Y	Y
State Controls	Y	Y
State FEs	Y	Y
Firm FEs	Y	Y
Year FEs	Y	Y
Obs.	17,596	18,718
Adj. R^2	0.727	0.694

Panel B. External Environmental Ratings

VARIABLES	(1)	(2)
	TOTAL_PAY $_{t+1}$	
SCAP*ENV_CONCERN_HIGH	**-0.152*****	
	(0.041)	
SCAP*ENV_RATING_LOW		**-0.109****
		(0.046)
SCAP	-0.022	0.039
	(0.024)	(0.040)
ENV_CONCERN_HIGH	-0.010	
	(0.025)	
ENV_RATING_LOW		0.073*
		(0.041)
Firm Controls	Y	Y
CEO Controls	Y	Y
State Controls	Y	Y
State FEs	Y	Y
Firm FEs	Y	Y
Year FEs	Y	Y
Obs.	12,888	4,279
Adj. R^2	0.683	0.707

Panel C. Internal Environmental Concerns

VARIABLES	(1)	(2)
	TOTAL_PAY $_{t+1}$	
SCAP*ENV_LAWSUIT	**-0.123****	
	(0.050)	
SCAP*STRANDED_ASSET		**-0.080***
		(0.043)
SCAP	-0.051***	-0.046**
	(0.019)	(0.020)
ENV_LAWSUIT	0.003	
	(0.032)	
STRANDED_ASSET		0.000
		(0.000)
Firm Controls	Y	Y
CEO Controls	Y	Y
State Controls	Y	Y
State FEs	Y	Y
Firm FEs	Y	Y
Year FEs	Y	Y
Obs.	25,267	25,267
Adj. R^2	0.683	0.683

Table 8. Heterogenous Effect: The Role of CEO Power and Corporate Governance

This table reports the results of the difference-in-differences regressions of CEO compensation (*TOTAL_PAY*) on *SCAP* indicator, conditional on CEO power and proxies of corporate governance. In Panel A, we examine the role of CEO power. *CEO_TENURE_LONG* is a dummy variable that equals one if the CEO tenure of a firm in year *t* is longer than 10 years and otherwise equals zero; *CEO_OWN_LARGE* is a dummy variable that equals one if the CEO ownership of a firm is more than 5% in year *t* and otherwise equals zero. In Panel B, we examine the role of corporate governance. *HHI_LOW* is a dummy variable that equals one if Text-based Network Industry concentration (TNIC) Herfindahl-Hirschman Index (HHI) of a firm is below the median value in year *t* and otherwise equals zero; *TSIM_HIGH* is a dummy variable that equals one if the TNIC Total Similarity Index is above the median value in year *t* and otherwise equals zero; *HOSTILE_HIGH* is a dummy variable that equals one if the Hostile Takeover Index of a firm is above the sample median in year *t* and otherwise equals zero. All regressions control for firm-level, CEO-level, and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. CEO Power

	(1)	(2)
VARIABLES	*TOTAL_PAY* $_{t+1}$	
SCAP*CEO_TENURE_LONG	**0.072*** **	
	(0.026)	
SCAP*CEO_OWN_LARGE		**0.088** **
		(0.040)
SCAP	-0.073***	-0.061***
	(0.022)	(0.021)
CEO_TENURE_LONG	-0.035*	
	(0.020)	
CEO_OWN_LARGE		-0.095*
		(0.048)
Firm Controls	Y	Y
CEO Controls	Y	Y
State Controls	Y	Y
State FEs	Y	Y
Firm FEs	Y	Y
Year FEs	Y	Y
Obs.	25,267	25,267
Adj. R^2	0.683	0.683

Panel B: Corporate Governance

VARIABLES	(1)	(2) $TOTAL\_PAY_{t+1}$	(3)
SCAP*HHI_LOW	**-0.068****		
	(0.026)		
SCAP*TSIM_HIGH		**-0.049***	
		(0.025)	
SCAP*HOSTILE_HIGH			**-0.130***
			(0.066)
SCAP	-0.019	-0.030	0.061
	(0.019)	(0.023)	(0.057)
HHI_LOW	-0.010		
	(0.022)		
TSIM_HIGH		0.009	
		(0.019)	
HOSTILE_HIGH			0.021
			(0.046)
Firm Controls	Y	Y	Y
CEO Controls	Y	Y	Y
State Controls	Y	Y	Y
State FEs	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Obs.	23,968	23,968	17,484
Adj. R^2	0.681	0.681	0.664

Table 9. The Effect of SCAP Adoption on Managerial PPS and Risk-Taking Incentives

This table reports the results of the difference-in-differences regressions of managerial pay-for-performance sensitivity (*DELTA*) and risk-taking incentives (*VEGA*) on *SCAP* indicator. All regressions control for firm-level, CEO-level and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) *DELTA* $_{t+1}$	(2) *VEGA* $_{t+1}$
SCAP	**-0.075***	**-0.142***
	(0.043)	(0.078)
SIZE	0.150***	0.308***
	(0.031)	(0.045)
VOL	-0.095***	-0.135***
	(0.024)	(0.037)
RET	0.395***	0.104**
	(0.049)	(0.051)
ROA	0.803***	0.391***
	(0.145)	(0.064)
MTB	0.010***	0.002
	(0.002)	(0.001)
CASH	0.557***	0.056
	(0.160)	(0.156)
LEV	-0.333***	-0.093
	(0.083)	(0.105)
CAPX	1.497***	0.484
	(0.246)	(0.352)
CEO_AGE	-0.110	-0.692***
	(0.137)	(0.130)
CEO_TENURE	0.235***	0.103***
	(0.017)	(0.016)
STATE_GDP	-0.242	-1.189**
	(0.269)	(0.485)
STATE_GDPGR	1.043**	0.084
	(0.442)	(0.678)
STATE_GDPCAP	-0.757	-0.144
	(0.575)	(0.991)
State FEs	Y	Y
Firm FEs	Y	Y
Year FEs	Y	Y
Obs.	23,461	23,461
Adj. R^2	0.724	0.684

Table 10. The Effect of SCAP Adoption on Environmental Contracting

This table reports the results of the difference-in-differences regressions of the likelihood of environmental contracting adoption (*ENV_PAY*) and the number of environmental contracting related words (*LOG(1+ENV_PAY_COUNT*) on *SCAP* indicator. All regressions control for firm-level, CEO-level and state-level characteristics. All regressions also control for state, firm and year fixed effects. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*ENV_PAY* $_{t+1}$		*Log(1+ENV_PAY_COUNT)* $_{t+1}$	
	Probit	OLS	Tobit	OLS
SCAP	**0.224*** **	**0.076*** **	**0.177*** **	**0.083*** **
	(0.065)	(0.014)	(0.032)	(0.016)
SIZE	0.204***	0.037***	0.183***	0.047***
	(0.019)	(0.004)	(0.013)	(0.005)
VOL	-0.041	-0.011**	-0.032	-0.011*
	(0.028)	(0.005)	(0.019)	(0.006)
RET	0.265**	0.032	0.204**	0.017
	(0.122)	(0.020)	(0.090)	(0.019)
ROA	-0.327**	-0.050*	-0.278***	-0.057**
	(0.129)	(0.027)	(0.082)	(0.026)
MTB	-0.002	-0.000	-0.001	0.000
	(0.002)	(0.000)	(0.002)	(0.000)
CASH	0.183	0.020	0.163*	0.020
	(0.157)	(0.028)	(0.099)	(0.030)
LEV	0.103	0.038*	0.078	0.050**
	(0.108)	(0.022)	(0.071)	(0.024)
CAPX	0.597	0.200**	0.372	0.302***
	(0.469)	(0.087)	(0.282)	(0.095)
CEO_AGE	0.143	0.022	0.127	0.030
	(0.223)	(0.041)	(0.111)	(0.045)
CEO_TENURE	-0.033	-0.004	-0.031**	-0.007
	(0.025)	(0.005)	(0.014)	(0.005)
STATE_GDP	0.511	0.014	0.261	0.014
	(0.437)	(0.086)	(0.219)	(0.118)
STATE_GDPGR	-1.648***	-0.210**	-1.361***	-0.191**
	(0.418)	(0.087)	(0.309)	(0.090)
STATE_GDPCAP	2.231***	0.483***	2.079***	0.522***
	(0.527)	(0.105)	(0.268)	(0.144)
State FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Obs.	24,404	24,404	24,404	24,404

Appendix A

Table A1. Variable Definitions

Variable	Definition	Data Source
Panel A: Key Dependent Variables		
GSVI_CLIMATE	The level of Google Search Volume Index on the keyword *climate* of a state in a year.	Google Trend
ΔGSVI_CLIMATE	The changes in the level of Google Search Volume Index on the keyword *climate*.	Google Trend
ENV_RISK	An index of environment-related political risk as developed in Hassan et al. (2019). Yearly index is an average of the four quarterly indexes in the same year.	Hassen et al. (2019): https://www.firmlevelrisk.com/home
TOTAL_PAY	The natural logarithm of one plus CEO total compensation (TDC1).	ExecuComp
DELTA	The natural logarithm of one plus delta (i.e., the dollar change in CEO's wealth (in $000s) associated with a 1% change in the firm's stock price).	ExecuComp + CRSP
VEGA	The natural logarithm of one plus vega (i.e., the dollar change in CEO's wealth (in $000s) associated with a 1% change in the standard deviation of the firm's stock returns).	ExecuComp + CRSP
ENV_PAY	An indicator variable that equals one if a firm's proxy statement contains any environmental contracting words; otherwise equals zero. An environmental contracting word is define as a machine-learning-based environmental keyword is surrounded by a compensation-related keyword and an executive-related keyword.	DEF 14A Filings
Log(1+ENV_PAY_COUNT)	The natural logarithm of one plus the number of environmental contracting words.	DEF 14A Filings
CASH_PAY	The natural logarithm of one plus CEO cash-based compensation (SALARY + BONUS).	ExecuComp
EQUITY_PAY	The natural logarithm of one plus CEO equity-based compensation (OPTION_AWARDS_BLK_VALUE + RSTKGRNT + LTIP).	ExecuComp
CASH_PAY_RATIO	Ratio of CEO cash-based to total compensation (CASH_PAY/TOTAL_PAY).	ExecuComp
NON-CEO_TOTAL_PAY	The natural logarithm of one plus top5 executives' total compensation.	ExecuComp
Panel B: Key Independent Variable		
SCAP	Indicator for whether the firm's historical headquarter state finalizes the State Climate Adaptation Plan.	https://www.georgetownclimate.org/adaptation/plans.html
Panel C: Firm-level Control Variables		
SIZE	Natural log of total assets (AT).	Compustat
VOL	Standard deviation of the firm's daily stock returns calculated at yearly level.	CRSP
RET	Buy-and-hold return on the firm's stock over a year.	CRSP
ROA	Net income before extraordinary items and discontinued operations divided by total assets (IB/AT).	Compustat
MTB	Market-to-book ratio, where market equity is calculated by multiplying the closing share price (PRCC_F) by total shares outstanding (CSHO) and book equity is total common equity (CEO).	Compustat
CASH	Ratio of cash items to total assets (CHE/AT).	Compustat

LEV	Sum of current liabilities and long-term debt divided by total assets ((DLT+DLTT)/AT).	Compustat
CAPX	Ratio of capital expenditures to total assets (CAPX/AT).	Compustat
Panel D: CEO-level Control Variables		
CEO_AGE	Natural log of one plus CEO age.	ExecuComp
CEO_TENURE	Natural log of one plus CEO tenure.	ExecuComp
Panel E: State-level Control Variables		
STATE_GDP	Natural log of state gross domestic product.	U.S. Bureau of Economic Analysis
STATE_GDPGR	Growth rate in state gross domestic product over the prior year.	U.S. Bureau of Economic Analysis
STATE_GDPCAP	Natural log of state gross domestic product per capita.	U.S. Bureau of Economic Analysis
Panel F: Cross-sectional Variables		
SCAP_UNCERTAIN_HIGH	Indicator of below median SCAP goals	Ray and Grannis (2015)
GSVI_CLIMATE_HIGH	Indicator of above median *GSVI_CLIMATE* index	Google Trend
ENV_RISK_HIGH	Indicator of above median *ENV_RISK* index	https://www.firmlevelrisk.com/home
ENV_CONCERN_HIGH	Indicator of the firm's number of environmental concerns being above the cross-sectional median.	KLD/MSCI ESG STATS
ENV_RATING_LOW	Indicator variable that equals one if firms' environmental ratings from Sustainalytics is below the median value in year t and otherwise equals zero.	Sustainalytics
ENV_LAWSUIT	Indicator of the firm being involved as a defendant in an environmental lawsuit that starts in the current year.	AuditAnalytics
STRANDED_ASSET	Indicator of the firm's GICS industry of Metals & Mining; Oil, Gas & Consumable Fuels; Electric Utilities; Gas Utilities; Chemicals; Construction Materials; Independent Power and Renewable Electricity Producers; or Energy Equipment & Services.	Compustat
CEO_TENURE_LONG	Indicator variable that equals one if the CEO tenure of a firm in year *t* is longer than 10 years.	ExecuComp
CEO_OWN_LARGE	Indicator variable that equals one if the CEO ownership of a firm is more than 5% in year *t*.	ExecuComp
HHI_LOW	Indicator of the firm's TNIC HHI index being below the cross-sectional median.	https://hobergphillips.tuck.dartmouth.edu/industryconcen.htm
TSIM_HIGH	Indicator of the firm's TNIC Total Similarity index being above the cross-sectional median.	
HOSTILE_HIGH	Indicator of the firm's Hotile Takeover index being above the cross-sectional median.	https://pages.uoregon.edu/smckeon/

Table A2. Timelines of Finalizations of State Climate Adaptation Plan

No.	State	State Name	Year Finalized	No.	State	State Name	Year Finalized
1	AL	Alabama		27	MT	Montana	2020
2	AK	Alaska	2010	28	NE	Nebraska	
3	AZ	Arizona		29	NV	Nevada	
4	AR	Arkansas		30	NH	New Hampshire	2009
5	CA	California	2009	31	NJ	New Jersey	
6	CO	Colorado	2011	32	NM	New Mexico	
7	CT	Connecticut	2013	33	NY	New York	2010
8	DE	Delaware	2015	34	NC	North Carolina	2020
9	DC	D.C.	2016	35	ND	North Dakota	
10	FL	Florida	2008	36	OH	Ohio	
11	GA	Georgia		37	OK	Oklahoma	
12	HI	Hawaii		38	OR	Oregon	2010
13	ID	Idaho		39	PA	Pennsylvania	2011
14	IL	Illinois		40	RI	Rhode Island	2018
15	IN	Indiana		41	SC	South Carolina	
16	IA	Iowa		42	SD	South Dakota	
17	KS	Kansas		43	TN	Tennessee	
18	KY	Kentucky		44	TX	Texas	
19	LA	Louisiana		45	UT	Utah	
20	ME	Maine	2010	46	VT	Vermont	
21	MD	Maryland	2008	47	VA	Virginia	2008
22	MA	Massachusetts	2011	48	WA	Washington	2012
23	MI	Michigan		49	WV	West Virginia	
24	MN	Minnesota		50	WI	Wisconsin	
25	MS	Mississippi		51	WY	Wyoming	
26	MO	Missouri					

Table A3. Alternative Model Specifications: Pre-SCAP Propensity Score Matching

This table reports the results of the alternative difference-in-differences specifications, using propensity score matching (PSM) samples. The matching procedure is 1-to-1 nearest neighbor (within 1% caliper and with replacement) on all firm/CEO/state characteristics measured one year prior to SCAP finalization year. The control firms are never-treated and headquartered in either both neighboring and non-neighboring states (Panels A and B) or only neighboring states (Panels C and D) with at least one SCAP-adopting state. *TREATED* is an indicator of treated firms, and *POST* is an indicator of post-SCAP years. All regressions control for firm-level characteristics, while some regressions control for CEO-level characteristics and state-level characteristics. All regressions also control for state, firm (or industry) and year fixed effects, but their estimates are suppressed for brevity. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Post-match Diagnostic Test (Neighboring & Non-neighboring Controls)

VARIABLE	Treated	Control	t test
SIZE	7.346	7.368	-0.210
VOL	-3.665	-3.733	1.755
RET	0.034	0.041	-0.836
ROA	0.005	0.031	-2.616
MTB	2.386	2.391	-0.017
CASH	0.222	0.210	1.077
LEV	0.179	0.177	0.171
CAPX	0.035	0.040	-1.938
CEO_AGE	4.017	4.021	-0.482
CEO_TENURE	1.828	1.773	1.135
STATE_GDP	13.383	13.195	4.094
STATE_GDPGR	0.023	0.038	7.825
STATE_GDPCAP	10.726	10.646	10.949

Panel B: DiD Test (Neighboring & Non-neighboring Controls)

	(1)	(2)	(3)
VARIABLES		*TOTAL_PAY* $_{t+1}$	
TREATED*POST	**-0.084********	**-0.080********	**-0.083****
	(0.030)	(0.030)	(0.031)
TREATED		Absorbed by the fixed effects	
POST	0.043	0.040	0.046
	(0.035)	(0.035)	(0.035)
SIZE	0.257***	0.255***	0.256***
	(0.024)	(0.024)	(0.024)
VOL	-0.026	-0.027	-0.028
	(0.026)	(0.027)	(0.026)
RET	0.241***	0.240***	0.239***
	(0.053)	(0.052)	(0.052)
ROA	0.381***	0.372***	0.370***
	(0.081)	(0.080)	(0.080)
MTB	0.004**	0.004**	0.004**
	(0.001)	(0.001)	(0.001)
CASH	-0.071	-0.075	-0.076
	(0.120)	(0.121)	(0.121)
LEV	-0.387***	-0.383***	-0.381***
	(0.084)	(0.084)	(0.083)
CAPX	0.323	0.295	0.282
	(0.290)	(0.292)	(0.292)
CEO_AGE		-0.175**	-0.169**
		(0.075)	(0.075)
CEO_TENURE		0.034***	0.034***
		(0.012)	(0.012)
STATE_GDP			-0.181
			(0.180)
STATE_GDPGR			0.670
			(0.492)
STATE_GDPCAP			0.187
			(0.315)
State FEs	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Obs.	13,351	13,351	13,351
Adj. R^2	0.669	0.669	0.669

Panel C: Post-match Diagnostic Test (Neighboring Controls)

VARIABLE	Treated	Control	t test
SIZE	7.822	7.520	1.905
VOL	-3.971	-4.011	0.818
RET	0.033	0.039	-0.564
ROA	0.043	0.050	-0.756
MTB	2.467	1.952	0.932
CASH	0.180	0.180	-0.004
LEV	0.200	0.224	-1.110
CAPX	0.034	0.039	-1.170
CEO_AGE	4.046	4.037	0.759
CEO_TENURE	1.882	1.906	-0.319
STATE_GDP	13.010	12.349	10.594
STATE_GDPGR	0.024	0.027	-0.993
STATE_GDPCAP	10.761	10.559	14.317

Panel D: DiD Test (Neighboring Controls)

	(1)	(2)	(3)
VARIABLES		*TOTAL_PAY* $_{t+1}$	
TREATED*POST	**-0.114****	**-0.116****	**-0.105****
	(0.055)	(0.054)	(0.050)
TREATED		Absorbed by the fixed effects	
POST	-0.045	-0.044	-0.060
	(0.047)	(0.047)	(0.046)
SIZE	0.423***	0.421***	0.421***
	(0.037)	(0.038)	(0.038)
VOL	-0.064***	-0.063***	-0.063***
	(0.023)	(0.023)	(0.023)
RET	0.284***	0.286***	0.284***
	(0.079)	(0.080)	(0.080)
ROA	0.452***	0.457***	0.457***
	(0.140)	(0.138)	(0.137)
MTB	0.005**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)
CASH	0.142	0.146	0.151
	(0.185)	(0.180)	(0.181)
LEV	-0.104	-0.104	-0.106
	(0.163)	(0.162)	(0.161)
CAPX	0.343	0.355	0.358
	(0.353)	(0.348)	(0.346)
CEO_AGE		0.085	0.086
		(0.187)	(0.187)
CEO_TENURE		-0.015	-0.016
		(0.040)	(0.040)
STATE_GDP			0.357
			(0.392)
STATE_GDPGR			0.636
			(0.604)
STATE_GDPCAP			-0.609
			(0.535)
State FEs	Y	Y	Y
Ind FEs	Y	Y	Y
Year FEs	Y	Y	Y
Obs.	6,900	6,900	6,900
Adj. R^2	0.565	0.565	0.565

Table A4. The Effect of SCAP Adoption on Components of CEO Compensation

This table reports the results of the difference-in-differences regressions of cash-based, equity-based components, and ratio of cash-based component over CEO total compensation (i.e., *CASH_PAY*, *EQUITY_PAY*, and *CASH_PAY_RATIO*, respectively) on *SCAP* indicator. All regressions control for firm-level, CEO-level and state-level characteristics. All regressions also control for state, firm and year fixed effects, but their estimates are suppressed for brevity. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
VARIABLES	$CASH\_PAY_{t+1}$	$EQUITY\_PAY_{t+1}$	$CASH\_PAY\_RATIO_{t+1}$
SCAP	**-0.066****	**-0.121***	**0.004**
	(0.026)	(0.067)	(0.006)
SIZE	0.093***	0.027	-0.035***
	(0.020)	(0.043)	(0.006)
VOL	-0.032***	0.021	0.004
	(0.011)	(0.039)	(0.004)
RET	0.195***	0.202	-0.008
	(0.035)	(0.155)	(0.010)
ROA	0.170***	0.132	-0.056**
	(0.054)	(0.113)	(0.024)
MTB	-0.001	0.001	-0.001**
	(0.001)	(0.002)	(0.000)
CASH	-0.282***	-0.482	-0.070***
	(0.072)	(0.483)	(0.021)
LEV	-0.085	-0.655***	0.074***
	(0.057)	(0.152)	(0.016)
CAPX	-0.477**	-0.340	-0.172***
	(0.204)	(0.587)	(0.060)
CEO_AGE	0.123	-0.168	0.090***
	(0.135)	(0.240)	(0.030)
CEO_TENURE	0.005	-0.030	-0.004
	(0.011)	(0.027)	(0.004)
STATE_GDP	0.433	1.329*	0.053
	(0.276)	(0.718)	(0.060)
STATE_GDPGR	0.509	-0.748	-0.039
	(0.525)	(0.859)	(0.148)
STATE_GDPCAP	-0.501	-1.020	0.061
	(0.365)	(1.169)	(0.121)
State FEs	Y	Y	Y
Firm FEs	Y	Y	Y
Year FEs	Y	Y	Y
Obs.	25,267	25,267	25,176
Adj. R^2	0.597	0.763	0.530

Table A5. The Effect of SCAP Adoption on Non-CEO Executive Compensation

This table reports the results of the difference-in-differences regressions of non-CEO executive compensation (*NON-CEO_TOTAL_PAY*) on *SCAP* indicator. All regressions control for firm-level, CEO-level and state-level characteristics. All regressions also control for state, firm and year fixed effects, but their estimates are suppressed for brevity. The robust standard errors clustered at the headquarter state level are provided in parentheses. A detailed description of the variable construction is provided in the Appendix Table A1. The symbols *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*NON-CEO_TOTAL_PAY* $_{t+1}$			
SCAP	**-0.084*** **	**-0.066*** **	**-0.063*** **	**-0.064*** **
	(0.027)	(0.021)	(0.021)	(0.020)
SIZE		0.237***	0.230***	0.229***
		(0.013)	(0.013)	(0.013)
VOL		0.011	0.012	0.012
		(0.013)	(0.014)	(0.013)
RET		0.170***	0.169***	0.168***
		(0.030)	(0.031)	(0.031)
ROA		0.192***	0.184***	0.182***
		(0.051)	(0.052)	(0.052)
MTB		0.005***	0.005***	0.005***
		(0.001)	(0.001)	(0.001)
CASH		0.093*	0.096*	0.097*
		(0.048)	(0.051)	(0.050)
LEV		-0.193***	-0.192***	-0.193***
		(0.042)	(0.042)	(0.042)
CAPX		0.463***	0.428***	0.427***
		(0.128)	(0.130)	(0.131)
CEO_AGE			0.071	0.069
			(0.048)	(0.048)
CEO_TENURE			0.048***	0.048***
			(0.008)	(0.008)
STATE_GDP				0.099
				(0.171)
STATE_GDPGR				0.215
				(0.464)
STATE_GDPCAP				-0.102
				(0.228)
State FEs	Y	Y	Y	Y
Firm FEs	N	Y	Y	Y
Year FEs	Y	Y	Y	Y
Obs.	25,237	25,237	25,237	25,237
Adj. R^2	0.114	0.785	0.787	0.787

Table A6. Environmental Contracting Keyword List

Panel A. Seed words

Environmental related words:
From Flammer et al. (2019): energy_efficiency, environmental_compliance, environmental_goals, environmental_performance, environmental_projects, greenhouse_gas_reduction, sustainability
Other general environmental-related words: climate_risk, climate_change, carbon_emission, renewable_energy, air_pollution

Compensation related words:
compensation, pay, bonus, award, salary, incentive

Executive related words:
executive, ceo, neo

Panel B. Machine-learning-based (Word2vec) Top500 environmental keywords

Included: [398 words]
energy_efficiency, greenhouse_gas_emission_reduction, sustainability, climate_risk, climate_change, carbon_emission, renewable_energy, air_pollution, greenhouse_gas_emission, emission, energy_use, reduce_greenhouse_gas_emission, water_use, reduce_emission, environmental_sustainability, ghg_emission, greenhouse_gas, reduce_ghg_emission, carbon_footprint, reduce_carbon_footprint, greenhouse_gas_(_ghg_)_emission, water_usage, environmental_stewardship, environmental, clean_energy, climate_related, greenhouse_gas_ghg, energy_usage, ghg, energy_consumption, co2_emission, carbon_dioxide_emission, air_emission, environmental_social, reduce_environmental_footprint, deforestation, carbon, methane_emission, environmental_footprint, reduce_energy_consumption, house_gas, reduce_carbon_emission, social_environmental, waste_generation, pollution, environmental_social_governance, sustainability_initiative, food_waste, improve_energy_efficiency, sustainability_strategy, clean, water_consumption, water_footprint, waste, recycling_program, climate_change_risk, energy_water, fossil_fuel, carbon_management, biodiversity, global_warming, conserve_water, carbon_dioxide, water_efficiency, protect_environment, resource_use, energy_transition, climate_change_impact, environmental_impact, greenhouse_gas_ghg_emission, water_conservation, house_gas_emission, energy_efficient, resource_scarcity, sustainability_program, water, carbon_intensity, plastic_waste, environmental_social_governance_esg, conserve_energy, packaging_sustainability, waste_water, sustainably, packaging_footprint, waste_heat, sustainability_goal, reduction_target, air_quality, water_reuse, climate_impact, sustainability_issue, sustainability_related, transportation_support_program, emission_reduction, climate_related_risk, sustainable, cleaner_source, climate_and_water_impact, water_stewardship, waste_processing, transition_low_carbon_economy, carbon_reduction_strategy, planet, energy_and_water_use, waste_reduction_opportunity, carbon_neutral, renewable_energy_source, sustainability_service, energy_source, sustainable_agriculture, manure_management, conservation, sustainable_sourcing, resource_conservation_program, energy_efficiency_initiative, energy_conservation, water_conservation_effort, resource_conservation, food_waste_reduction, palm_oil, methane_loss, energy_efficiency_program, manufacturing_and_distribution_process, hydraulic_fracturing, waste_reduction, pesticide_use, sustainability_practice, packaging_initiative, energy_efficiency_opportunity, land_disturbance, freshwater_use, ghg_)_emission, carbon_strategy, environmentally, landfill_diversion, minimize_environmental_impact, energy_intensity, company_greenhouse_gas_emission, waste_minimization, grassland, waste_footprint, climate, fossil_base, reforestation_effort, waste_usage, climate_action, companys_energy_resource, water_utilization, water_reduction_target, greenhouse_gas_management, energy_efficiency_renewable, water_management, rubber_wood, emit, electricity_use, pollution_prevention, carbon_accounting, [ner:quantity]_co2, achieve_carbon_neutrality, waste_production, diversion_rate, recyclability, air_interstate_rule, toxic, clean_energy_future,

sustainability_effort, carbon_opportunity, emission_intensity, companys_environmental_footprint, renewable, waste_reduction_program, world_natural_resource, flaring, pesticide, environmentally_friendly, palm_oil_production, co2_carbon_dioxide, water_impact, ghg&rdquo, methane, issuesfrom_climate_change, fertilizer_use, water_savings, waste_diversion, air_emission_reduction, energy_management_work, water_need, landfill, renewable_energy_resource, sustainability_feature, carbon_future, heat_island_effect, water_scarcity, reduce_water_consumption, seismicity, flare, package_weight, grid_resiliency, facility_integrity, waste_reduction_effort, water_performance, habitat, carbon_dioxide_(_co2_)_emission_intensity, reusability, water_disposal, forest_management_practice, paper_reduction, carbon_intensity_cost, sustainability_report, resource_consumption, packaging, carbon_electricity_generation_resource, conserving_resource, pipeline_replacement, emission_management, water_constrain, recycl_content, water_risk, carbon_alternative, recycling_reuse, supplier_sustainability, wind_solar, carbon_world, warming_emission, palm_oil_plantation, water_consumption_practice, green, environmental_protection, carbon_dioxide_co2, energy_save, water_sustainability, clean_water, styrofoam, greenhouse_gas_matter, footprint, cleaner_fuel, renewable_source, fossil, recycling_and_composting_program, recyclable, climate_friendly, recycling_material, recycling_rate, renewable_resource, energy_resource, responsibility_related, carbon_neutrality_goal, companys_nuclear_energy_center, climate_change_strategy, reclamation_program, class_sustainability_practice, energy_standard, carbon_sequestration, material_recycling, electrification, material_usage, reuse_recycle, heat_loss, carbon_neutrality, nature_challenge, building_initiative, energy_demand, esg, linen_and_towel_reuse_program, greenhouse_gas_(_ghg_)_emission_reduction_target, energy_efficiency_target, stormwater_management, steelmaking_process, energy, companys_environmental_impact, refrigerant_leak, forest_conservation, carbon_reduction_matter, emission_intensity_reduction_target, soil_health, storm_water_runoff, hazard, prevention_effort, resource_stewardship, pollution_prevention_program, climate_change_challenge, fleet_emission, climate_change_solution, wood_fuel, decarbonization, solar_wind, air_and_water_quality, climate_resilience, sustainable_packaging, packaging_goal, mineral_sourcing, climate_related_risk_opportunity, freshwater_intake, water_waste, climate_preparedness, co2, greenhouse_gas_intensity, eor, fuel_demand, tomorrow_energy_need, wastewater_management, emission_reduction_target, climate_change_initiative, ghg_emission_reduction, air_pollutant_emission, carbon_related, landfill_space, csr_performance, water_management_practice, deforestation_risk, water_strategy, fuel_emission, recycling_paper, esg_)_principle, disposal_solution, recycling_effort, compostable, energy_opportunity, water_reduction_goal, electricity_consumption, sustainability_/_corporate_responsibility, ghg_goal, business_travel_emission, sustainability_performance, companys_environmental_performance, power_plant, methane_emission_management, sustainability_and_social_responsibility_effort, energy_vision, climate_footprint, green_building, water_runoff, water_access, climate_challenge, carbon_free_resource, water_pollution, solar, climate_goal, freshwater_requirement, forestry_practice, sustainability_matter, single_use_plastic, sustainability_reporting, freshwater_supplies, generation_resource, water_stress, conservation_project, water_use_reduction, waste_reduction_measure, wildfire_risk, burning, energy_and_water_usage, fossil_fuel_base, minimize_waste, carbon_energy_solution, prevent_pollution, product_sustainability, pellet_loss, energy_policy, fossil_fuel_industry, water_requirement, carbon_goal, treatment_utility, low_carbon_economy, micro_turbine, energy_independence, esg_)_strategy, stewardship_commitment, sustainability_advantage, rainwater_harvesting, solid_waste, commitment_sustainability, carbon_neutral_airline, resource_depletion, co2_emission_reduction, motion_sensor_lighting, efficiency_upgrade, energy_reduction, ash_management, sustainable_forestry, sustainability_challenge, recycling_process, oil_and_gas_combustion, ecomagination, plant_automation, forest_stewardship, ecological, waste_recycling, disaster_preparedness, carbon_generation, energy_efficiency_project, vehicle_charging_infrastructure, carbon_and_methane_emission, iso_14001_standard, energy_sourcing, waste_and_greenhouse_gas_(_ghg_)_emission, packaging_waste, carbon_reduction_effort,

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Excluded: [102 words]

community_impact_matter, scope_[ner:cardinal], casing, societal, human_rights, science_base, supply_chain, diversity_inclusion, animal_welfare, infrastructure, company_aspiration, human_health, indoor_environment, coffee_supply_chain, pollinator_health, alcohol_responsibility, consumption, community_resiliency, 2&ordm, use_phase, office_initiative, sound_government_policy, denim_and_wove_bottom_factory, cocoa_community, value_chain, term_economic_viability, across_value_chain, youth_opportunity, women_economic_empowerment, resilience, pepsicos_supply_chain, freight_shipping, smallholder_farmer, gender_equality, harm_product, report%20of%20the%20subcommittee%20on%20, employee_and_community_relation, paper_purchase_policy, sulfur_hexafluoride, repair_leak, companys_impact, initiativethe, target_initiative, cost_effective_opportunity, food_safety, food_system, supply_chain_responsibility, rate_case_strategy, fight, tailing_management, resiliency, racial_equity, tackle, beef_sustainability, supply_chain_oversight, impact_area, performance_optimization, space_efficiency, hygiene_education, barley, child_safety, nrg_strategy, hunger_prevention, property_efficiency, food_acceptability, chain_sustainability, nutrient_management, product_impact, litigation_new_york_case, animal_well_being, healthcare_disparity, supply_chain_compliance, material_area, health_,_safety_and_wellness_program, diversity_equity, employee_stress, capital_effort, rate_competitiveness, combat, chicken_slaughter, community_well_being, sbt, demand_management, market%20, product_safety, odc, stakeholder_engagement, net_economic_cost, state_economy, supply_chain_transparency, product_and_non_product_action, business_and_[ner:gpe], tobacco_grow, response_protocol, sequestration_facility, crisis_response_initiative, reliable_affordable, improve_efficiency, ldar, stakeholder_expectation, world_effort, worker_welfare, pepsicos_performance, frace, community_garden, coffee_production, paint_system, meter_infrastructure, gas_infrastructure_operation, sulfur_dioxide_nitrogen_oxide,

Appendix B. Details of Measuring Environmental Contracting Using Machine Learning

1. DEF 14A Proxy Statements

We use Word2vec (Mikolov et al., 2013), a machine learning framework, to construct a measure on whether corporate executive compensation is linked to environment (i.e., environmental contracting, or E-pay) based on a firm's proxy statement (SEC Form DEF 14A), which is an important material that a public-listed firm is required to provide before the annual meeting to help shareholders improve understanding on corporate governance related issues (e.g., voting procedure, nomination of board of directors and role of committees). Crucially, proxy statements provide detailed information on executive compensation, from which we can know the compensation structure of top executives, such as base salary, bonus, and stock awards, and the performance metrics used for performance-based incentives.

We first use a Python program to web scrape available DEF 14A filings from SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database from 1994 to 2021. In this step we obtain 180,453 raw texts of proxy statements. We then link the filings to ExecuComp database, from which we successfully match 54,758 proxy statements to 3,724 unique firms.

Similar to corporate financial statements (SEC Form 10K), the raw texts of proxy statements contain substantial portions of HTML code, ASCII-encoded graphics, and embedded PDFs that are not the focus of our study. Thus, we follow Loughran and McDonald (2014) to preprocess the raw texts filings using regular expression. Specifically, we remove all ASCII-encoded sections containing the following tags: *<TYPE>GRAPHIC*, *<TYPE>ZIP*, *<TYPE>EXCEL*, *<TYPE>JSON*, *<TYPE>PDF*, *<TYPE>XML*. Next, we further remove the sections with the following HTML tags: *<PDF>*, *<XML>*, *<XBRL>*, *<DIV>*, *<TR>*, *<TD>*, and *<FONT>*. In addition, the SEC header and footer (i.e., *<SEC-HEADER>* and "-----*END PRIVACY-ENHANCED MESSAGE*-----") which include basic information about firms are also removed as these are out of our interest. We further replace *\ * and *\ * with a blank space and *\&AMP* and *\&#38* with "*&*". Lastly, consistent with Loughran and McDonald (2014), we remove all the extended character references and the remaining markup tags (i.e., <…>).[27]

[27] The instruction of extended character references is in the section "5.2.2.6 Extended Character Sets within HTML Documents" here: https://www.sec.gov/info/edgar/specifications/edgarfm-vol2-v59.pdf. The cleaning procedure is tightly following the parsing details provided by Bill McDonald from his personal website: https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/10x-stage-one-parsing-documentation/. We thank Bill for generously make the instruction publicly available.

2. Why *Word2vec*

Words are hard to be quantified. Prior studies commonly represent words in one-hot vectors.[28] However, one-hot vector has three limitations. First, the vector size will become enormous when the size of the text data increases. Second, it does not contain any semantics but is a simple numeric representation. Third, one-hot vector is very sparse and thus cannot be used to compute similarity among words. Word2vec, a machine learning architecture (Mikolov et al., 2013), is widely applied to address the issues of one-hot vectors for the reasons that: i) it is similar to the singular value decomposition method that projects high dimensional vectors to low dimension (Levy and Goldberg, 2014); ii) it produces semantic word embeddings from a neural network model and thus each word vector can represent the meaning itself; and iii) word vectors are dense and thus can be used to compute similarity among the words.

The *Word2vec* model is based on the distributional hypothesis that "You should know a word by the company it keeps" (Firth, 1957), which suggests that words that occur with similar neighboring words should have similar meanings. Based on this linguistic idea, Mikolov et al. (2013) use neural networks to predict the neighboring words for each focal word, and the parameter matrix obtained from the hidden layer is a semantic vector representation of every word.[29] Figure B1 illustrates the simple neural network framework for the *Word2vec* model, where the focal word is used to predict only one neighboring word. Specifically, a focal word w_c is first initialized as $1\times V$ one-hot vector in the input layer of the neural networks, where V represents the number of the unique words in the corpus. Next, w_c is projected into v_w, a $1\times N$ hidden layer by multiplying the $1\times V$ one-hot vector with the $V\times N$ parameter matrix W, where N is a dimension of interest which generally varies from 50 to 1000. Please note that the parameter matrix W actually contains the dimensionality reduced word embeddings for each word. The previous step is to transform the initial one-hot vector to the corresponding vector v_w (word embedding) in W.

On the next stage, v_w is further multiplied by the other $N\times V$ parameter matrix W', which will produce $v_{w'}$, a $1\times V$ prediction vector in the output layer. We then use Softmax function to transform $v_{w'}$ to w_{c+j} which is a vector of probabilities that predicts the neighboring word for the focal word w_c.[30] We will try to maximize the probability of predicting the correct neighboring word for the focal word with the following equation:

[28] One-hot vector is a 1×N vector which consists of a single 1 used to identify the focal word in a text and all others 0. For example, a sentence "What is one-hot vector" has four unique words. Each word can be represented as a 1×4 one-hot vector: *What* is [1 0 0 0]; *is* is [0 1 0 0]; *one-hot* is [0 0 1 0]; *vector* is [0 0 0 1].

[29] *Word2vec* has two different model architectures to produce the vector representation. One is called Continuous Skip-gram (SG), which is to use the focal (center) word to predict the neighboring words. The other is called Continuous Bag of Words (CBOW), which is to use neighboring words to predict the focal (center) words. Please see Mikolov et al. (2013) for more details.

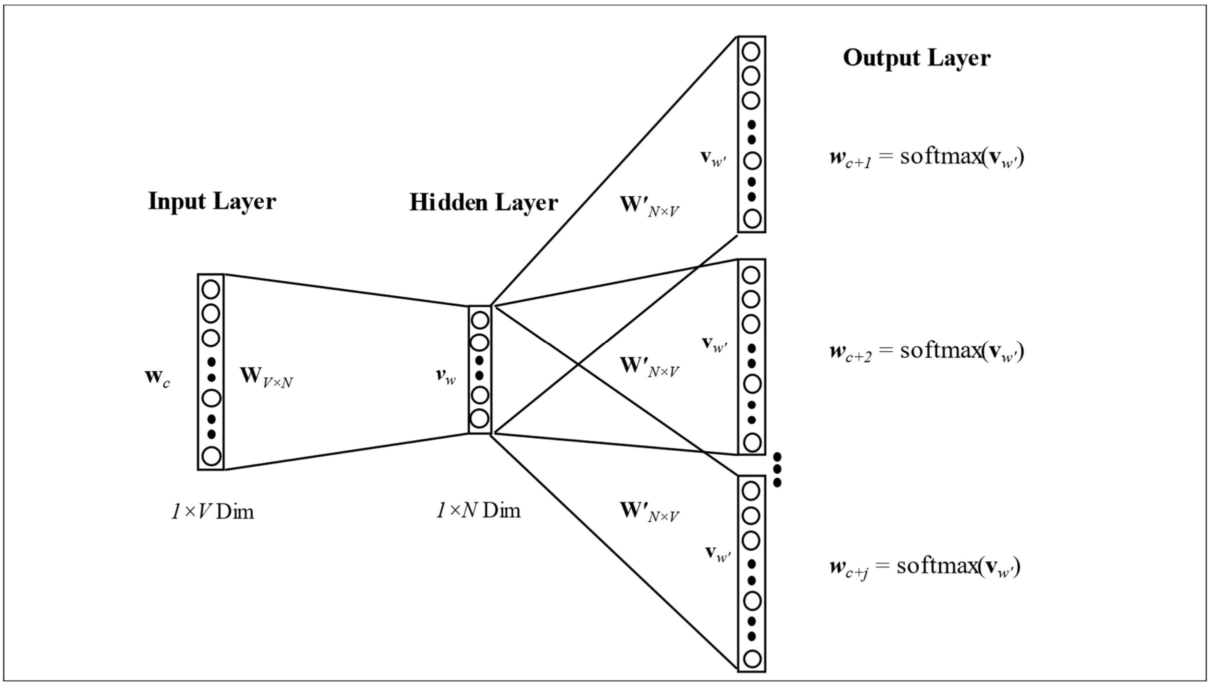
[30] The purpose of using Softmax function is to transform a vector of numbers into a vector of probabilities, restricting the numbers to range from zero to one. The probability of each value is proportional to the relative proportion of each value in the vector.

$$(W, W') = P(w_{c+j} | w_c)$$

$$= \prod_{c=1}^{V} \prod_{\substack{-m \le j \le m \\ j \ne 0}} P(w_{c+j} | w_c; W, W') \tag{1}$$

where m is the window size of the context, W_c is the focal word at location c, W and W' are two parameter matrices that are initialized randomly before the training stage. When the training process starts, we will first feed forward each word in the corpus to the neural network, which will predict the neighboring words correspondingly. The model will make mistake, i.e., the predicted neighboring words are not the ground truth. After the feed-forward process, the model will then feed backward (the so-called backpropagation) to fine tune the parameter matrices W and W' to reduce the prediction error. The best parameters should maximize the probability in Equation (1). After rounds of iterations, the prediction error will converge and the two parameter matrices will become stable. *Word2vec* will then use the average of V_W and $V_{W'}$ as the word embedding representation for each word when the training process is finished. Thus, by applying the *Word2vec*, we can generate word embeddings with the vector size of N to quantify each word. The word embeddings contain the semantics of the word and are dense, allowing us to expand a list of keywords that are having high similarity scores with the seed words so that the measurement underestimation issue by the pre-specified keyword approach can be addressed.

Figure B1. Neural Network Framework for *Word2vec*



3. Data Preprocessing and Word2vec Model Implementation

We use Stanza (Qi et al., 2020), a Python natural language processing toolkit for linguistic analysis of different human languages such as English and Chinese, to parse the proxy statements.[31] Following Li et al. (2021), we first split the raw text of proxy statements into tokens and sentences.[32] We then do lemmatization for words, transforming them back to the dictionary forms.[33] As proxy statements contain voluminous information on named entities (e.g., organization name, date, location, and person's name) which are not the focus of our study, we further apply the named entity recognition processor in Stanza to replace those named entities with tags (see, e.g., Loughran and McDonald, 2014; Li et al., 2021).[34] Next, as prior research documents that text classification performance could be improved when using n-grams compared with unigrams (Tan, Wang, and Lee, 2002; Bekkerman and Allan, 2004), we follow the approaches proposed by Routledge, Sacchetto, and Smith (2018) and Li et al. (2021) to identify n-grams from the earnings transcripts.

Specifically, we first employ the dependency parser in Stanza to analyze the syntactic dependency relationships between words. Figure B2 illustrates the parsed sentence "We love teaching as well as doing research." by Stanza. The word *as well as* is a multiword expression and tagged by the parser as *fixed*, which is one of the three relations (the other two are *flat* and *compound*) for multiword expressions according to the Universal Dependencies Relations.[35] We thus identify the multiword expressions if words are in one of the above three relations, and further connect them with underscore to stand for a single word (e.g., *as well as* will be transformed to *as_well_as* in the transcripts). Second, for the remaining words that are not identified by Stanza as multiword expressions, we further employ the *phrases* models of *gensim* library in Python to automatically detect bigrams and trigrams in the transcripts. It is built based on the merit that words that are frequently co-occurred to above a certain threshold will be treated as multiword expressions.[36] After the parsing stage, we remove the punctuation

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[31] Stanza supports more than 70 languages for natural language analysis and is trained with neural network models. It contains different neural pipelines to help users preprocess the text data, such as sentence segmentation, dependency parsing, and sentiment analysis. Please see https://stanfordnlp.github.io/stanza/index.html for more information about the package.

[32] We should segment earnings transcripts into sentences because the *Word2vec* operates at sentence level.

[33] For example, "We went to a conference yesterday" will be lemmatized to "We go to a conference yesterday".

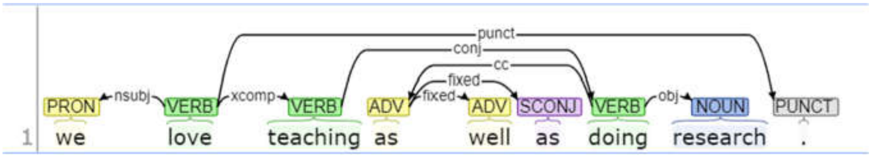
[34] For example, "We plan to go to U.S." will be replaced as "We plan to go to [NER: LOC]".

[35] *fixed* is used to represent for fixed grammaticized expressions (e.g., *because of*, *as well as*, and *rather than*). *flat* is used to represent for exocentric semi-fixed multiword expressions such as names (e.g., *Mr. Robert*) and numbers (e.g., *five hundreds*). *compound* is used to represent for noun compounds (e.g., *dollar loan*), verb compounds (e.g., *put up*), and adjective compounds (e.g., *intellectual property*). Please see https://universaldependencies.org/u/dep/ for more information about Universal Dependencies.

[36] The following formula is used by the model to calculate the score of potential multiword expression: $score(w_i, w_j) = \frac{(count(w_i w_j) - \delta) \times |V|}{count(w_i) \times count(w_j)}$, where δ is the minimum value for the words to be treated as bigrams and $|V|$ is the length of the transcript. We follow Li et al. (2021) to set δ to equal to 50 (the default value is 10 in the model). We use a threshold of 10 (the default value in the model), which means that if the score of two words is lower than 10, then it will not be considered as bigrams. If two words are considered as bigram, then we again connect the two words with the underscore _ to transform them as a single word. The same procedures apply when we further detect trigrams using the *phrases* model. Please see https://radimrehurek.com/gensim/models/phrases.html for more information about *phrases* model and *gensim* library.

and stop words from the earnings transcripts.[37] The sentence preprocessing procedures are now completed.

Figure B2. Dependency Parsing



We next generate word embeddings using the *Word2vec* model framework in *gensim* library.[38] For the model parameter setting, we use a vector size of 300 for the word embeddings. We set up the minimum word count equal to 5, which means the rare words with lower than 5 occurrences in the sample transcripts will be ignored. We choose the default window size of 5, which is the maximum distance between the focal word and the predicted word in each sentence. We select the Skip-gram (SG) with negative sampling approach for model training. Negative sampling is a method to speed up the training process while also improve the prediction performance (Mikolov, 2013). Finally, we choose the number of epochs to be 50, which indicates that the *Word2vec* model will iteratively go over the whole text of transcripts for 50 times to adjust and stabilize the word embedding parameters. A higher number of epochs could reduce more of prediction error and thus the word embeddings could be more representative. After the training process is completed, our *Word2vec* model contains 642,365 unique word embeddings with size of 300.

3. Pre-specified Seed Words and Expanded word list

First, we follow Flammer, Hong, and Minor (2019) and use their seven environmental-related words as seed words: *energy efficiency*, *environmental compliance*, *environmental goals*, *environmental performance*, *environmental projects*, and *greenhouse gas emissions reductions*. In addition, we further add the following five words that are unambiguously related to environment but are not included in Flammer, Hong, and Minor (2019)'s keyword list: *climate risk*, *climate change*, *carbon emission*, *renewable energy*, and *air pollution*. Please note that the selected keywords may not be observed in our sample of proxy statements. For example, if the word *environmental goals* is not used in any one of the proxy statements, then the *Word2vec* model will not produce this word vector. In this case, our algorithm will ignore this non-exist word and use the remaining existed words as seed words. Panel A of Table A6 in Appendix A presents the initial environmental keyword that are used in our study.

Next, we feed the 12 seed words into the self-trained *Word2vec* model and obtain an expanded list of keywords that are having high cosine similarity scores with the seed words. Specifically, the

[37] We obtain the list of generic stop words from Bill McDonald personal website https://sraf.nd.edu/textual-analysis/stopwords/. We thank Bill for making the resource publicly available.
[38] Please see https://radimrehurek.com/gensim/models/word2vec.html for more information about the model architecture in *gensim*.

Word2vec model will first generate a seed word vector $\overline{V_{SW}}$, which is computed by taking the average of the vectors of the 12 environmental seed words.[39] The model will then calculate the cosine similarity scores between $\overline{V_{SW}}$ and the vector of each unique word in the filings. A higher similarity score indicates that the word's meaning is closer to those of 12 environmental seed words. We follow Li et al. (2021) to select the top500 words that are having highest cosine similarity scores with $\overline{V_{SW}}$ as our expanded word list.

Nevertheless, we find that for those top500 words, not all of them are closely related to environment. For example, *human rights*, *diversity inclusion*, and *product safety* are included in the top500 word list, but they are explicitly not related to environment.[40] To reduce the Type II error (false positives), each of the authors manually screen the 500 words and determine whether they are related to environment or not. We only keep a word if all of us agree that it is unambiguously environmental related. After conducting screening and thorough discussion, we drop unrelated words out of the expanded word list and our final keyword list, $\mathbb{E}$, has 398 environmental related words. Panel B of Table A6 in Appendix A presents the included and excluded keywords.

4. Measuring the Adoption of Environmental Contracting

After obtaining an expanded list of environmental words from *Word2vec*, we then construct a measure to capture a firm's adoption of environmental contracting. The prior studies manually search pre-specified keywords in the Executive Compensation section, or Compensation Discussion and Analysis (CD&A) section of each proxy statement to determine whether a firm uses CSR (ESG) contracting or not (see., e.g., Flammer, Hong, and Minor, 2019; Qin and Yang, 2022). However, there are two concerns for this approach. First, unlike traditional financial statements (e.g., SEC Form 10K) that each section is itemized, the titles of sections of proxy statements are not either itemized or standardized, making it hard for researchers to use computer programs to extract a standalone section from proxy statements.[41] As we aim to construct the environmental contracting measure for a broader sample of firms included in Execucomp and for a whole period from 1994-2021 (prior studies only construct the measure limit to S&P 500 firms and in a short period of years), it requires an enormous amount of human effort to manual screen the Executive Compensation or CD&A sections of proxy

[39] As aforementioned, it is likely not every one of the 12 seed words will occur in proxy statements. In this case, the averaged vector will be constructed using the remaining existed seed words instead.

[40] Rather, they are more related to the social dimension of the Environmental, Social, and Governance (ESG) Criteria. It somehow makes sense why *Word2vec* will regard these words as similar to environmental-related keywords because CEOs generally talk about ESG matters in the same contexts.

[41] For example, Section Item 1.A of a 10K filing is Risk Factors. Thus, we can easily extract the Risk Factors section by requiring the text to be within Item 1.A and Item 1.B. However, it is not the case in proxy statements. For example, in Apple Inc.'s 2021 DEF 14A filing, the Section Compensation Discussion and Analysis (CD&A) is not itemized followed by the Section Compensation Committee Report. While in Meta Platforms, Inc.'s 2021 DEF 14A filing, the CD&A is followed by the Section Perquisites and Other Benefits. Thus, to the best of our knowledge, we could not find a clean way to extract a standalone section from proxy statements. See, https://www.sec.gov/Archives/edgar/data/0000320193/000119312521001987/d767770ddef14a.htm and https://www.sec.gov/Archives/edgar/data/0001326801/000132680122000043/meta2022definitiveproxysta.htm.

statement, to decide whether a firm uses environmental contracting in every year, which we think a manual job for this task is not achievable. A second issue of this approach is that assume that we can extract, or manual screen the Executive Compensation section from the whole proxy statement for each firm, the environmental words that are observed in Executive Compensation may not be in the context of discussing executive pays to environment, and may only act as an emphasis of corporate environmental consciousness, as we know that firms start to mention more green words to signal the capital market that they are caring about corporate sustainability. Thus, only searching environmental words in these sections to decide the adoption of environmental contracting is not accurate.

To address the above concerns, we still use the whole textual content of each proxy statement to construct the measure, while we do improvement to tackle with the issue that the environmental words are not relating to managers discussing about compensation. We utilize a window approach, similar to Hassen et al. (2019), by requiring the environmental words be surrounded by compensation and executive related words. Specifically, we further construct two pre-specified keyword lists. The first list contains compensation related words: *compensation*, *pay*, *bonus*, *award*, *salary*, and *incentive*, while the second list contains executive related words: *executive*, *CEO*, and *NEO*.[42]We then determine a firm i has adopted environmental contracting in year t if there is at least one environmental related word e appeared in firm i's proxy statement in year t, and if there are also at least one compensation-related word and at least one executive related word appeared within 10 words before and after the environmental word e. The model is as follows:

$$ENV\_PAY_{it} = \mathbb{1}[e \in \mathbb{E}] \times \mathbb{1}[|e - c| < 10] \times \mathbb{1}[|e - m| < 10] \quad (1)$$

where $\mathbb{1}[\cdot]$ is an indicator function, $\mathbb{E}$ is the set of machine-learning-based environmental keywords, c is the position of the nearest compensation synonym, and m is the position of the nearest executive synonym. The *ENV_PAY* is in fact an indicator variable that determines whether a firm adopts environmental contracting in a specific year. It will equal one if we identify at least one machine-learning-based environmental word that occurs in proximity to (within 10 words) the compensation and executive synonyms, and otherwise equal zero.[43] This measure ensures that the environmental words that we capture from the proxy statements of firms are used in the context of discussing executive compensation related issues and not the others, and also addresses the technical issue that the executive compensation section cannot be extracted alone from proxy statements. In addition to the indicator variable *ENV_PAY*, we also construct the other measure, *Log(1+ENV_PAY)* by counting the number of environmental words that indicate environmental contracting to capture a firm's mentioning intensity.

[42] We do not use *Word2vec* to further expand the compensation and executive word lists because we believe the two lists of keywords can sufficiently capture words that related to compensation and executive.

[43] For example, *ENV_PAY* will equal one for the sentence "Our executive compensation structure emphasizes on corporate environmental performance", and it will equal zero for the sentence "We care corporate environmental performance".

After constructing the measure, we merge with the sample used in our study. We successfully merge with 24,404 firm-year observations.

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