Climate-linked Pay and Supply Chain Management[1]

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Abstract

This study documents a positive and significant association between a firm's use of climate-linked metrics in executive pay and its outsourced emissions to the supply chain. Using a sample of 870 listed U.S. firms, I find that firms with better internal corporate governance, better financial performance, and lower growth opportunities are more likely to use climate-linked pay. Such pay schemes are followed by an increase in upstream suppliers' emissions, and a decrease in firms' direct emissions. This effect is more pronounced among firms with greater climate pressure, greater bargaining power over suppliers, and lower external monitoring. To explore potential mechanisms, I show that firms with climate-linked pay facilitate emissions outsourcing by initiating (terminating) fewer (more) contracts with suppliers from regions with higher emissions costs. Overall, my findings highlight the potential impact of climate-linked metrics in executive compensation on the supply chain.

Keywords: ESG metrics; climate-linked pay; executive compensation; outsourcing; supply chain management; switching costs

JEL Classifications: G30, M12, M14, M41

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1. Introduction

In light of the growing awareness of Environmental, Social, and Governance (ESG) issues among stakeholders, a rising number of companies have been striving to demonstrate their commitment to sustainability. One corporate practice is to link executive compensation to ESG-related performance. Such compensation contracts allow firms to credibly convey to various stakeholders that management will draw attention to ESG practices. The 2021 Institutional Shareholder Services (ISS) ESG report suggests that the percentage of Russell 3000 firms linking executive pay to ESG metrics has grown from 7 percent in 2018 to over 20 percent in 2021.[1]

The literature on the consequences of nonfinancial metrics in executive compensation, however, is limited in that they predominantly focus on the corporate outcomes within focal firms. These consequences include greater innovation productivity, higher employee well-being (Tsang et al. 2021), better ESG ratings (Ikram et al. 2019), and higher firm value and shareholders' returns (Abdelmotaal and Abdel-Kader 2016; Flammer et al. 2019). In this study, I examine whether the use of "E" (i.e., environmental) or climate-linked metrics in executive pay is associated with subsequent greenhouse gas (GHG) emissions outsourcing along the upstream supply chain. I focus on emissions outsourcing because it is a common operating decision (Tully 1994). Compared with the direct emissions generated by firms, outsourced emissions receive less public attention (Edmans 2021; Ritz 2022), which allows firms to shift their irresponsible practices to their overseas suppliers (e.g., Surroca et al. 2013; Lee et al. 2014; Ben-David et al. 2021). However, outsourcing is not always an optimal competitive strategy and may hurt firm performance due to additional transport costs, governance, and pair

[1] See the ISS report at https://www.isscorporatesolutions.com/file/documents/ics-incentivizing-what-matters.pdf

searching costs (Grossman and Helpman 2002; Grossman et al. 2005). Therefore, it is unclear whether the use of climate-linked pay leads to emissions outsourcing.

To study this research question, I start with a sample of 7,330 S&P 1500 U.S. firm-year observations from 2006 to 2020 with available proxy statements. Following prior literature (Flammer et al. 2019; Ikram et al. 2019; Cohen et al. 2023), I manually search for climate-related keywords in metrics from the Compensation, Discussion, and Analysis (CD&A) section of firms' proxy statements. I identify that a firm practices climate-linked pay if it incorporates at least one climate metric as a key performance indicator in executive pay. On average, around 5 percent of the observations in my sample use climate-linked pay, and this percentage has increased over threefold, rising from 2.6 percent in 2006 to approximately 8 percent in the year 2020. Such pay schemes are most prevalent in the energy, materials, and utilities industries.

To measure emissions along the supply chain, I follow the GHG Protocol, which classifies GHG emissions into three categories based on the sources, namely Scope 1, 2, and 3 emissions.[2] In this study, I focus only on the upstream Scope 3 emissions that capture emissions from suppliers.[3] An average firm in the sample experiences a steady decline in Scope 1 (Scope 3) emissions by 7 percent (3 percent) from 2006 to 2020 as a result of energy efficiency improvements, technological innovations, and increased reliance on renewable energy.

One empirical challenge in my study is that climate-linked incentives are often vague in metrics without specific or assessable objectives (Bebchuk 2022), i.e., implicit about the sources of emissions. In this study, I assume that climate-linked metrics are more relevant to Scope 1 emissions than to Scope 3 emissions. I validate this assumption by testing the CEO compensation consequences for firms using climate-linked pay. I find that CEO cash compensation is significantly higher in firms with a lower proportion of Scope 1 emissions but

[2] Scope 1 emissions are direct greenhouse emissions generated by focal firms. Scope 2 emissions are indirect greenhouse emissions associated with the purchase of electricity, steam, heat, or cooling. Scope 3 emissions are indirect emissions generated by firms from both the upstream and downstream supply chain of the focal firm.

[3] In this study, I use "Scope 3 emissions" and "upstream Scope 3 emissions" interchangeably.

is irrelevant to Scope 3 emissions. Comparatively, the CEO cash compensation is insensitive to either Scope 1 or Scope 3 emissions among firms without climate-linked pay.[4] This evidence suggests that, to the extent that climate-linked pay signals the board's priority in improving firms' ESG consciousness, managers with climate-linked pay have greater incentives to substitute Scope 1 emissions with Scope 3 emissions.[5]

I first examine the determinants of using climate-linked pay. Consistent with the literature on the determinants of nonfinancial incentives (Ittner et al. 1997; Chen et al. 2015; Hong et al. 2015; Cohen et al. 2023), my results suggest that firms with a higher level of internal corporate governance, better financial performance, and lower growth opportunities are more likely to include climate-linked metrics in executive pay.

In my main tests, I examine the association between climate-linked pay and emissions outsourced to the upstream suppliers, measured as the upstream Scope 3 emissions. I find that climate-linked pay is positively (negatively) associated with upstream Scope 3 (Scope 1) emissions, suggesting that climate-linked pay leads to emissions shifting to the supply chain. In terms of economic significance, firms with climate-linked pay are associated with Scope 3 emissions that are 19.8 percent, 10.3 percent, and 2.9 percent higher, when scaled by total assets, total sales, and total emissions, respectively, than their peers without climate-linked pay. Cross-sectional analyses show that the associations between climate-linked pay and emissions outsourcing are primarily driven by firms with higher climate pressure, higher bargaining power over suppliers, and lower external monitoring.

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[4] I focus on cash compensation as 94.7 percent of S&P 500 firms with ESG-linked pay include ESG metrics as part of the short-term incentive plans. See the 2021 WTW Report https://www.wtwco.com/en-us/insights/2022/01/use-of-esg-metrics-in-executive-incentive-plans-expanding. In untabulated table, my results continue to hold using total compensation.

[5] Holmström 2017 discusses multitasking in contract design where agents take into account the interdependencies among multiple tasks and allocate their attention accordingly. In Section V, I discuss and show no evidence that the climate-linked pay affects pay-for-financial-performance sensitivity or brings substantial changes in financial performance around the first-time adoption of climate-linked pay. They suggest that the financial task and climate task are not perfect substitutes nor complements, and therefore this study continues to focus on the management of single climate task.

I adopt a multi-pronged approach to mitigate self-selection bias. First, I exploit two instrumental variables: the use of climate-linked pay by client firms served by the same compensation consultant (Gallani 2016, Choi 2021) and the use of climate-linked pay by firms sharing the same constituency statutes (Flammer 2019). Both variables capture peer effects on focal firms' use of climate-linked pay but have no direct impact on the focal firm's operating decisions. The instrumental variable methods yield qualitatively similar results. Second, my results also hold in a stacked Difference-in-Differences (DiD) analysis around the first time when firms adopt climate-linked pay. Collectively, these tests mitigate the concern that differences between firms with and without climate-linked pay drive my main results.

Next, I perform three tests on supplier switching as a potential mechanism for emission outsourcing. First, I find that firms with climate incentives initiate (terminate) fewer (more) contracts with suppliers in countries/jurisdictions facing higher emissions costs. Second, I leverage exogenous changes in suppliers' home country ESG regulations and show that firms with climate-linked pay substantially reduce new suppliers from countries which mandated ESG reporting. Third, I validate the supplier-switching mechanism by showing that the association between climate-linked pay and emissions outsourcing is concentrated in firms with lower supplier-switching costs. Taken together, the evidence thus far suggests that firms with climate-linked pay facilitate emissions outsourcing through strategic supplier switching.

I also perform a battery of robustness and additional tests. First, from the upstream supplier's perspective, if a large portion of its customers use climate-linked pay and outsource their emissions upstream, the focal firm (supplier) would experience an increase in Scope 1 emissions. My results confirm this conjecture. Second, revenue-linked pay may lead firms to overly produce and outsource productions, i.e., emissions, to their supply chains (Fershtman and Judd 1987; Bloomfield 2021). I find no evidence supporting this alternative explanation.

Third, I use total indirect emissions (including Scope 2 and upstream Scope 3 emissions) as an alternative measure for emissions outsourcing, and the results are robust to this specification.

This study contributes to the literature on how executives manage performance to meet or beat pre-established performance goals in two ways. First, prior studies focus on managing financial performance to meet financial targets, such as meeting or beating analysts' consensus forecasts (Bartov et al. 2002) and avoiding losses (Burgstahler and Dichev 1997). This is the first study to show that executives manage climate-related performance to meet compensation plan goals. Second, this study is related to the literature on the link between pay and performance. Prior studies show that using *explicit* financial goals may provide incentives for management to just beat the targets (e.g., Bettis et al. 2013; Bennett et al. 2017). My results highlight the costs of having *implicit* nonfinancial goals (i.e., implicit sources of emissions) in executive pay: such climate-linked incentives may lead managers to game the pay system by increasing the use of a less salient form of emissions.

My study also contributes to the emerging literature on the effect of ESG metrics in managerial compensation on corporate policies and outcomes. Prior studies primarily focus on the consequences of such incentives within the focal firms, and they tend to be mostly beneficial (e.g., Tsang et al. 2021; Flammer et al. 2019; Ikram et al. 2019). I find a potential negative externality in supply chains. My study documents that climate-linked pay triggers emissions spillovers into the supply chain and impacts supplier switching decisions. Presumably, the board adopts climate metrics in executive pay in response to global climate change. My results suggest that the current compensation design has not achieved the goal of reducing overall emissions and that the effective use of climate-related metrics requires more careful design and greater board oversight to minimize executives' manipulation.

Finally, I consider executive compensation as a new dimension in the determinants of corporate decisions on pollution outsourcing. A substantial literature in climate finance documents substitutional relationships between firms' own emissions and outsourced emissions in response to regulatory changes faced by focal firms (e.g., Li and Zhou 2017; Ben-David et al. 2021; Dai et al. 2022). I show that executive compensation is another driving factor of emissions outsourcing. Thus, this research bridges these strands of literature by documenting the real effects of climate-linked executive incentives on firms' strategic allocation of emissions along the supply chain.

The remainder of the paper proceeds as follows. Section 2 summarizes the relevant literature and develops my hypothesis. Section 3 describes the sample and the key variables. Section 4 presents the research design and empirical results. Section 5 provides the robustness and additional tests, and Section 6 concludes the paper.

2. Prior Literature and Hypothesis Development

2.1 Determinants and Consequences of Nonfinancial Compensation Metrics

Firms use nonfinancial measures in executive incentives, such as customer satisfaction, corporate culture, product safety, diversity, and employee pay etc. The literature offers several reasons why firms select nonfinancial measures in their executives' contracts. Both agency theory (Jensen and Meckling 1976; Grossman and Hart 1980) and stakeholder theory (DiMaggio and Powell 1983; Meyer and Rowan 1977) suggest that an optimal executive contract induces managers to take actions that can help improve firm value. However, the managerial power theory suggests that when managers have excessive power and become "entrenched," agency costs are much more likely to occur at the expense of shareholders (e.g., Shleifer and Vishny 1989). Nonfinancial metrics are a potential mechanism for increasing executive compensation above the level justified by a firm's economic performance (Tedeschi and Reiss 2013; Schlenker 1980). Accordingly, most studies on the consequences of nonfinancial incentives focus on whether such compensation schemes represent agency costs. Abdelmotaal and Abdel-Kader (2016) find ESG-linked pay to be positively associated with shareholder returns. Flammer et al. (2019) establish causal evidence that the adoption of such pay practices increases firm value and long-term orientation and improves a firm's ESG performance. Ikram et al. (2019) find that firms with ESG-linked pay have better ESG ratings. Tsang et al. (2021) find that ESG-linked pay increases employee well-being and innovation productivity. Collectively, the literature argues that nonfinancial incentives change corporate decisions and enhance shareholders' and stakeholders' value of focal firms.

2.2 Performance Management and Supply Chain Management

While most studies in the preceding discussion focus on the consequences within the focal firm that uses nonfinancial incentives, it remains unexplored whether and how nonfinancial incentives may go beyond a firm's boundaries and exert impacts on outside partners. Specifically, climate-linked pay may lead firms to outsource emissions to their suppliers for two reasons.

First, prior studies find that the use of performance provisions in executive contracts may incentivize managers to manage reported performance. Theoretical evidence suggests that agents can manipulate observable financial metrics in optimal contracts (Baker 1992; Crocker and Slemrod 2008; Guttman et al. 2006). Empirical studies also support this argument by finding that managers with income-reporting incentives are more likely to manage discretionary accruals (e.g., Healy 1985; Bergstresser and Philippon 2006), or make suboptimal business decisions (e.g., Bennett et al. 2017; Roychowdhury 2006). Compared to financial metrics, nonfinancial metrics lack reliable tracking, reporting and verification, and thus are potentially more biasedly measured and prone to managerial manipulation (Eccles and Mavrinac 1995; Thomas et al. 2020). Such ambiguity in measurement may exacerbate manipulations in a multitasking model in which the agent opportunistically allocates her time and effort (Holmström and Milgrom 1987). Consistent with this argument, recent studies document a disagreement in ESG rating agencies, which makes it difficult to link CEO compensation to ESG performance (Berg et al. 2022; Christensen et al. 2022). Given such measurement noise, executives with climate-linked pay may optimize for one particular aspect while underperforming on other issues, that is, switching from direct emissions to indirect emissions.

Second, emissions outsourcing could be a channel of nonfinancial performance manipulation through which executives could achieve the targets in their incentive contracts. Outsourcing is not uncommon in many industries, including computers, automobiles, and food and beverages (Tully 1994). Empirical studies in climate finance literature have found evidence that firms shift their carbon emissions in a cross-state or cross-country setting. For example, U.S. firms reduce their carbon footprints by outsourcing emissions to states or countries with weak environmental regulatory enforcement when domestic expectations for compliance raise production costs at home (e.g., Ben-David et al. 2021; Bartram et al. 2022; Li and Zhou 2017). Studies in the operation management literature find that firms transfer socially irresponsible practices to overseas subsidiaries (e.g., Surroca et al. 2013), and significant regulatory changes in firm environmental requirements can generate uncertain leakage in the upstream supply chain (Lee et al. 2014). Firms with climate-linked pay could game the pay system by increasing the use of a less salient form of emissions by outsourcing.

In this study, I posit that the use of climate-linked pay attracts managers' attention to the direct emissions of focal firms, leading managers to manage climate performance by shifting emissions to their suppliers. Accordingly, I hypothesize that climate-linked pay leads firms to outsource their emissions to their upstream suppliers.

H1: Firms with climate-linked pay outsource emissions to the upstream suppliers.

However, this hypothesis is not without tension. First, outsourcing may not always be beneficial. Firms offshoring are burdened by extra transport costs or higher pair searching costs (Grossman and Helpman 2002; Grossman et al. 2005). The cost efficiency of outsourcing is also subject to the competition and negotiation positions of the focal firms (Feng and Lu 2012). Second, in a multi-tasking contract, the time that the agent spends on emission management may increase the marginal cost of value creation, thus generating limited incentives for executives to opportunistically manipulate emissions outsourcing and modify the supply chain strategy (Holmström 2017).[6] Third, despite the potential opportunism, focal firms with climate-linked pay might be incentivized to work closely with suppliers to reduce carbon emissions from every party along the supply chain (Song et al. 2022). Hence, the effect of climate-linked pay on emissions outsourcing is an empirical question to be examined.

3. Sample and Key Variables

3.1 Sample Selection

Table 1 Panel A describes the sample selection process. I start with 18,011 S&P 1500 U.S. publicly listed firm-year observations from 2006 to 2020 with proxy statements. The sample starts from 2006 because the U.S. Securities and Exchange Commission (SEC) passed a new rule in 2006 requiring public firms to provide more detailed summaries and discussions of their compensations for top executives. I require a firm-year to have available information on all control variables used in the main analyses. My final sample consists of 7,330 observations about 870 U.S. firms. Note that the resulting sample only includes firm-level characteristics excluding supply chain and country-year level data. The number of observations varies across analyses, given the different model specifications and data availability.[7]

Table 1 Panel B presents the sample distribution by industry. Not surprisingly, energy, materials and utilities are the industries that are most active in linking executives' pay to

[6] The amount of climate-linked pay may also disincentivize emission outsourcing. Of the total compensation paid to S&P 500 CEOs in 2021, around 8.6 percent was based on E&S performance, with most of the compensation still tied to financial performance. See https://corpgov.law.harvard.edu/2022/03/23/es-metrics-and-executive-compensation/.

[7] My main results are robust to a subsample from 2006 to 2015 given that the emission data was largely expanded since the beginning of 2016. Results remain qualitatively similar using a subsample from 2016 to 2020 given that the rising prevalence of climate-linked pay in recent years. Taken together, my findings are less likely to be driven by potential sample selection bias. Tables are reported in Online Appendix Table OA1.

climate-related metrics.[8] Other industries commonly adopting climate-linked pay include consumer service, household products, semiconductors, telecommunication, real estate, etc.

3.2 Measurement of Climate-linked Pay

To define climate-related metrics, I start with the metrics provided by Flammer et al. (2019) and Ikram et al. (2019) and expand them with more recently emerging climate-related keywords, such as “CO2”, “decarbonization”, “footprint”, etc.[9] Next, I hand collect the climate-linked metrics used by firms in proxy statement to create an indicator variable, *ClimateLink*, which takes the value of one if any executives have any grants tied to at least one climate-related metric, and zero otherwise. In the Online Appendix OA1, I provide several examples of climate-linked pay from the proxy statements.[10] On average, around 5 percent of observations in my sample use climate-linked metrics in executive compensation, which is consistent with the summary statistics in prior literature (e.g., Cohen et al. 2023). **Figure 1** depicts the time series of the percentage of firms that use climate-linked metrics in executives' incentive contracts. The percentage of firms with climate-linked pay rises from 2.6 percent in 2006 to around 8 percent in 2020.

3.3 Measurement of Emissions

The GHG Protocol standards classify emissions into three categories based on their sources: Scope 1 emissions directly generated in all production and operations of facilities owned or controlled by the firm; Scope 2 emissions from the consumption of purchased heat, steam, and electricity; and Scope 3 emissions indirectly caused by firm's activities but from sources not owned or controlled by the firm. The Scope 3 emissions can be further separated

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[8] To mitigate the potential selection bias resulted from the skewed industry distribution of climate-linked pay, I restrict the sample to emissions-intensive industries only, namely mining, manufacturing, and utilities, and employ a propensity-score-matching (PSM) method with replacement and a calliper of 0.01. My main results are still robust to this specification and reported in Online Appendix Table OA2.

[9] I disclose the full list of climate-linked keywords in Online Appendix OA2.

[10] Consistent with argument, most firms in my sample that disclose the use of climate goals do not specify the accurate definitions or measurements of those goals. I expect the climate-related incentives to at least represent the board's commitment to addressing climate issues but leave great discretion for manipulation.

into upstream and downstream emissions. I obtain GHG emissions from Bloomberg and Refinitiv.[11] **Figure 2** plots the time series trend of emissions for different measures. Both Scope 1 and Scope 3 emissions have been decreasing over the years, but the percentage of Scope 3 emissions has been increasing. Specifically, there is an obvious decrease (increase) in Scope 1 and Scope 3 emissions (percentage of Scope 3 emissions) in 2016, the first year after the Paris Agreement was signed in 2015. **Figure 2** shows that firms are switching to Scope 3 emissions, although the raw levels of Scope 1 and Scope 3 emissions have been dropping over the years.

3.4 Other Variables

I obtain financial fundamentals from COMPUSTAT and stock returns from CRSP. I also collect executive compensation from EXECUCOMP and board information from BOARDEX. **Table 2 Panel A** reports the summary statistics for the main regression sample. Approximately 5 percent of the observations in my sample incorporate climate metrics into executives' incentives. An average firm has a Tobin's Q of 1.72, a ROA of 0.107, an annual stock return of 0.090, a leverage ratio of 0.276, and a sales growth rate of 5 percent. On average, 29.2 percent of executives take seats on boards and 82 percent of directors on boards are independent. **Table 2 Panel B** reports the summary statistics of the samples partitioned by the use of climate-linked pay. It shows that firms with climate-linked pay are larger in size and lower in growth.

4. Research Design and Main Findings

4.1 Determinants of Climate-linked Pay

I estimate a Probit model to investigate the determinants of climate-linked pay.

$$P(ClimateLink_{i,t}) = Controls_{i,t-1} + FEs + \epsilon_{it} \quad (1)$$

[11] Concerns have been raised that data vendors adopt machine learning models to estimate environmental impacts for a company's own operations and across its supply chain if a firm does not disclose emissions data voluntarily. Aswani et al. (2023) find that stock returns are correlated with unscaled emissions estimated by Trucost but not with actually disclosed by firms. In my untabulated analysis, my results are robust to using emissions only self-disclosed by firms.

The dependent variable $ClimateLink$ is an indicator variable that takes a value of one if any executive has any grants tied to at least one climate-related performance, and zero otherwise. The control variables are all lagged by one year and fall into three categories: corporate governance measures, managerial power measures, and firm fundamentals.

First, I include two proxies for corporate governance. If shareholder theory or stakeholder theory is true, it can be observed that better corporate governance increases the likelihood of firms linking executives' pay to climate performance. *BOARDIND* indicates the percentage of independent directors on a board. *INST* is the institutional ownership.

Second, I include $EXECDIR$, the percentage of executives sitting on the board, as a proxy for managerial power. The managerial power theory suggests that managers with excessive power may use nonfinancial contracting to enhance the legitimacy of their compensation contracts and improve their reputations in the eyes of shareholders. Hence, I do not have a prior prediction of managerial power variables without knowing whether climate performance represents an agency cost or enhances shareholder value.

Third, I include a set of firm fundamentals. *SIZE* is the natural logarithm of total assets. *LEV* is the ratio of total debt to total assets. *CASH* is the cash equivalents scaled by average total assets. *TOBINQ* captures firm growth opportunities and is measured as the sum of the market value of equity and the book value of debt scaled by total assets. *ROA* and *RET* capture firm performance, defined as earnings before interest and taxes scaled by the average total assets, and annual stock returns, respectively. Following prior studies (e.g, Ittner et al. 1997), *STRATEGY* captures a firm's "prospector" strategy. I calculate an average value over the prior five years for these three firm-level proxies: the R&D-to-sales ratio, the market-to-book ratio, and the employees-to-sales ratio. I then aggregate these characteristics using factor analysis to construct a parsimonious measure of firm-level business strategy. As different business strategies may exist simultaneously within industries, it is important to capture a firm's position on the strategy continuum relative to firms within the same industry (Bentley et al. 2013). Hence, I construct an industry-adjusted firm-level strategy composite measure by subtracting the industry-averaged strategy factor score from the firm-level strategy factor score. I also include the volatility of financial measures. The agency theory suggests a negative relationship between the noise in a performance measure and the weight of the measure in executive compensation packages (Banker and Datar 1989). A few empirical studies support these theories by finding positive relations between the noise in accounting measures and the weight of nonfinancial measures in incentive contracts (e.g., Lambert and Larcker 1987; Bushman et al. 1996; Itter et al. 1997; Chen et al. 2015). Hence, I measure the noise in earnings by *NOISE*, calculated as the time-series standard deviation of the GIC industry-median ROA over the previous five years.

I also include two measures of the peer effects. First, firms' incentive contracts affect the design of another firm's incentive contract through a shared compensation consultant (Gallani 2016, Choi 2021). Hence, I include *CONSULT.PERCT*, calculated as the number of firms linking executive pay to climate metrics that share the same compensation consultant with the focal firm divided by the number of firms served by the same compensation consultant with the focal firm. Second, constituency statutes affect firms' adoption of climate-linked pay. Constituency statutes are state-level enactments that allow corporate officers and directors to consider the interests of a variety of stakeholders in carrying out their fiduciary duties to the corporation. Under these statutes, a corporation's officers and directors are allowed to consider the interests of employees, customers, suppliers, the environment, the local community, and any other potentially affected constituency (e.g., Orts 1992). Flammer et al. (2019) find that firms are encouraged to link CSR criteria in executive compensation for the interests of nonfinancial stakeholders and, hence, pursue interests that are not restricted to the bottom line. However, one limitation of an indicator variable directly related to constituency statutes is that most states had already adopted constituency statutes way before my sample starts. To increase the variation, I construct another variable, *STATE.PERCT,* to capture the same level of legitimacy that firms share within the same state. It is calculated as the number of firms linking executives' pay to climate-related metrics whose headquarters are located in the same state as the focal firm divided by the number of firms whose headquarters are located in the same state as the focal firm.

Table 3 presents the Probit regression results for equation (1). Consistent with the shareholder and stakeholder theory, I find that firms with higher board independence are more likely to use climate-linked pay. I do not find climate-linked pay to be associated with the percentage of executives sitting on boards, suggesting that the use of climate-linked pay is less likely to be driven by managerial power. I also find a negative and significant coefficient on *TOBINQ,* showing that firms with lower growth opportunities are more likely to use climate-linked pay. Consistent with prior literature (e.g., Ikram et al. 2019), I find that firms with better financial performance and larger sizes are more likely to use climate-linked pay. Finally, I find that climate-linked pay is positively associated with two peer effects. However, I find no significant associations between the prior noise in earnings or firms' strategy and the use of climate-linked pay. One possible explanation is that the insignificant coefficients on some of the control variables are due to low statistical power because I focus on the use of climate-related measures, unlike prior research, which use all nonfinancial measures in contracts (Ittner et al. 1997; Said et al. 2003; Chen et al. 2015). [12]

In summary, my results suggest that firms with a higher level of board governance, better firm performance and lower growth opportunities are more likely to incorporate climate performance in executives' contracts, which is consistent with prior literature (Hong et al. 2015)

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[12] I additionally control firms' emissions in the previous year in equation (1) and report the regression results in Online Appendix Table OA3. Results suggest that the use of climate-linked pay is insensitive to firms' emissions.

that climate activities are more likely to be beneficial to shareholders as opposed to a form of managerial excess or an agency cost.

4.2 Climate-linked Pay and GHG Emissions Outsourcing

4.2.1 Baseline Results

Next, I employ the following specification to explore the effect of climate-linked pay on firms' GHG emissions.

$$SCOPE3_{i,t} = \beta_1 ClimateLink_{i,t-1} + Controls_{i,t-1} + FEs + \epsilon_{it} \qquad (2)$$

The dependent variable is $SCOPE3$, which takes three forms: Scope 3 emissions scaled by total assets, Scope 3 emissions scaled by total sales, and the percentage of Scope 3 emissions out of total emissions.[13] Since there is little theory on what determines the level of GHG emissions, especially regarding their different sources, I follow Bolton and Kacperczyk (2021) to include an additional set of variables, including *INVEST* (capital expenditure scaled by average total assets), *HHI* (Herfindahl-Hirschman index at GIC level), *PPE* (plant, property, and equipment scaled by average total assets), and *SALESGTH* (sales growth rate), and the relevant control variables included in equation (1). Additionally, I also control for the Scope 1 emissions in the previous year which proxies for the salient emitting pressure, and the Scope 1 emissions in the current year which captures the contemporaneous operating decision. Finally, I include year and industry fixed effects.[14]

Table 4 reports the OLS results of equation (2). In Column (1) to (3), I find a positive and significant association between Scope 3 emissions and *ClimateLink*. In terms of economic significance, I find that firms with climate-linked executive pay are associated with Scope 3

[13] Aswani et al. (2023) raises concerns for unscaled emissions as they are largely a proxy for firm size and emissions scaled by size loses its predictive power for returns. They suggest that the emissions intensity is a better metric favored by industry, reflecting the ratio of emissions to assets or sales.

[14] Industries are defined by the 6-digit GIC industry groupings. The use of industry as opposed to firm fixed effects is standard in the supply chain literature (e.g., Raman and Shahrur, 2008; Costello, 2013; Cen et al., 2017). As discussed by Cen et al. (2017), the limited within-firm variation of the variable of interest (in my case, climate-linked pay) would make the inclusion of firm fixed effects problematic.

emissions scaled by assets that are 19.76 percent higher (i.e., a firm with *ClimateLink* has Scope 3 emissions scaled by assets that are 0.283 higher than the sample mean of 1.432, or 19.76 percent) Scope 3 emissions scaled by sales that are 10.25 percent higher, and Scope 3 emissions scaled by total emissions that are 2.93 percent higher than their peers who do not use climate-linked pay. Not surprisingly, Scope 3 emissions are also overall positively associated with firm ROA and contemporaneous Scope 1 emissions. On the other hand, the Scope 3 emissions are lower for firms with higher capital expenditure, larger size, and higher leverage.

4.2.2 Instrumental Variable Approach

To address the potential self-selection bias of *ClimateLink*, I estimate a Probit-2SLS[15] regression using two instrumental variables: *CONCULT.PERCT* and *STATE.PERCT*. The critical criterion for a good instrument is that it is correlated with the endogenous variable (i.e., *ClimateLink*) but exogenous (i.e., uncorrelated with the error terms in equation (2) above). I expect these two instrumental variables to be exogenous because the choice of compensation consultants and the location of headquarters is predetermined and unlikely to directly affect firms' emissions.[16]

Table 5 Panel A reports the Probit-2SLS results of equation (2). In Column (1) to (3), I find a positive and significant association between Scope 3 emissions and *ClimateLink*, consistent with my hypothesis. At the bottom of **Table 5 Panel A**, I report the F-statistic that passes the weak instrument test. The Hausman test rejects the consistency of OLS estimates, indicating that the endogeneity should be accounted for.

[15] Considering my endogenous variable *ClimateLink* is binary, I applied Probit-2SLS model which yields more efficient and robust estimator of ATE compared with direct 2SLS model (Woodridge 2010). Suppose $y = \omega + x$, and $P(\omega) = z + x$. The detailed steps are as the following:

(1) Apply a probit of ω on x and z, thus getting $\widehat{\omega}$, the predicted probability of ω.
(2) Estimate an OLS of ω on $(1, x, \omega)$, thus getting the fitted values $\omega_{2fv,i}$
(3) Estimate a second OLS of y on $\{1, x, \omega_{2fv,i}, \omega_{2fv,i}(x - \mu_x)\}$

[16] I estimate Scope 3 emissions on instrumental variables and other endogenous variables as shown in the Online Appendix Table OA4. I do not find a significant association between the dependent variable and the instrumental variables, which could alleviate a bit the concern on validity of instrumental variables. I also plot the geographical distribution of the use of climate-linked pay and the emissions outsourcing in Online Appendix Figure OA1 and I do not find the two distributions to be similar.

Table 5 Panel B reports the overidentifying restrictions test statistics (Sargan test) by regressing the second-stage residuals on our instruments and control variables. As discussed in Larcker and Rusticus (2010), if the instruments are valid, I expect the coefficients on our instruments and the R2 from the model to be close to zero. The panel shows that the F-statistic for the coefficients on instruments being jointly zero is insignificant.

In **Table 5 Panel C**, I estimate the effect of climate-linked pay on Scope 1 emissions. Similar to equation (2), I control Scope 3 emissions in the current year to capture the contemporaneous operating decisions. Overall, I find a significantly negative relationship between climate-linked pay and Scope 1 emissions. Collectively, these results suggest that firms with climate-linked pay shift their direct emissions to suppliers.[17]

4.3 Cross-sectional Analyses

4.3.1 GHG Emissions Outsourcing and Climate-related Pressure

In this section, I explore the heterogeneity of the main regression results of equation (2). First, I posit that firms with higher climate-related pressure have greater incentives to outsource emissions to their supply chains when using climate-linked pay. I use ESG scores from Refinitiv to measure firms' overall intentions, efforts and investments in improving ESG-related performance. Accordingly, low performers in ESG scores face higher pressure to turn "green". I split the sample based on the annual median of ESG score and estimate equation (2) respectively. The results are reported in **Table 6 Panel A**. Compared with Column (1) to (3), I find larger and positive coefficients on *ClimateLink* in Column (7) to (9) for firms with lower ESG scores, suggesting that firms with lower ESG scores are more likely to outsource emissions to their supply chain when using climate-linked pay.

[17] In my untabulated results, I do not find the use of climate-linked pay to be significantly associated with the total emissions, further suggesting that such pay contract only affects the allocation of emissions but not the overall emissions production.

As the second measure for climate-related pressure, I use the firm-level climate change exposure score from Sautner et al. (2023). A higher score reflects higher attention paid by earnings call participants to a firm's climate change exposure, which exerts greater pressure on a firm to enhance its climate change-related outcomes. I split my sample based on the annual median of the climate change exposure score, and the results are reported in **Table 6 Panel A.** I find larger and positive coefficients on *ClimateLink* among firms with higher climate change exposure in Column (4) to (6), compared with Column (10) to (12). Collectively, these results suggest that firms with lower climate performance scores or higher climate change exposure have greater incentives to outsource their emissions to the supply chain.[18]

4.3.2 GHG Emissions Outsourcing and Bargaining Power

Firms with large bargaining power can obtain higher outsourcing profits and are more likely to outsource (e.g., Plambeck and Taylor 2005; De Fontenay and Gans 2008). To measure focal firms' bargaining power, I use the natural logarithm of the number of suppliers as prior literature argues that the number of suppliers is associated with increased information and physical flows (Bozarth et al. 2009; Choi and Krause 2005). My second measure for bargaining power is supplier concentration. High supplier concentration lowers the bargaining power of purchasing firms and increases their exposure to supply shocks (Zhang et al. 2020). Following Chod et al. (2019), I calculate the supplier concentration as the Herfindahl-Hirschman index of supplier sales shares, which is computed for purchasing firm *i* as:

$$Suppliers\ Concentration = \frac{\sum_{j=1}^{n} Sales_{j,i}^{2}}{\left(\sum_{j=1}^{n} Sales_{j,i}\right)^{2}}$$

where *n* is the total number of suppliers, and $Sales_{j,i}$ represents the supplier *j*'s sales to the purchasing firm *i*'s total purchase. Due to the absent information regarding the sale of each

[18] I also split the sample by emission-intensive industries, i.e., utilities, mining, and construction and by Scope 1 emissions. Results are reported in Online Appendix Table OA5. The outsourcing induced by climate-linked pay is concentrated in emission-intensive industries and in firms with higher Scope 1 emissions.

supplier to the purchasing firm, Chod et al. (2019) suggest using the total sales of supplier *j* scaled by the total sales of all *n* suppliers to proxy for $Sales_{j,i}$. I obtain the U.S. dollar sales of international firms from the S&P Capital IQ database. A higher log number of suppliers and lower supplier concentration indicate higher bargaining power of purchasing firms. Next, I split the sample based on the annual median of supplier concentration and test equation (2).

Table 6 Panel B reports the Probit-2SLS regression results on subsamples split by bargaining power. Overall, I find larger and positive coefficients on *ClimateLink* among firms with a higher number of suppliers in Column (1) to (3), rather than a lower number of suppliers in Column (7) to (9). Similarly, I find positive and significant coefficients on *ClimateLink* in the subsample with lower supplier concentration in Column (10) to (12), while the same coefficients are mostly insignificant among the firms with high supplier concentration in Column (4) to (6). Collectively, these results indicate that the relationship between *ClimateLink* and the Scope 3 emissions is driven by firms with higher bargaining power over suppliers.

4.3.3 GHG Emissions Outsourcing and External Monitoring

Managers' ability to opportunistically manage performance is constrained by the effectiveness of external monitoring by stakeholders such as institutional investors or analyst coverage. Prior literature suggests that the presence of substantial external shareholdings in a firm can better deter management by its managers (e.g., Chung et al. 2002). As outsourcing activity induced by climate-linked pay is another format of performance manipulation, I posit that this relationship is subject to the level of external monitoring.

Table 6 Panel C presents the Probit-2SLS regression results on subsamples split by the annual median of external monitoring. I find larger, positive, and significant coefficients on *ClimateLink* for firms with a lower number of block institutional holders in Column (7) to (9), compared with firms with a higher number of block institutional holders in Column (1) to (3). Block institutional holders are defined as institutional investors whose ownerships exceed 5 percent of the total shares outstanding of the firm. Next, I obtain analyst data from IBES. Similarly, I also find that the positive and significant relationship between *ClimateLink* and Scope 3 emissions are driven by firms with lower analyst coverage in Column (10) to (12), rather than firms with higher analyst coverage in Column (4) to (6). Overall, these results are consistent in that external monitoring can better detect emissions management.

4.4 Test of Mechanism: Supplier Switching Decisions

In this section, I investigate how firms with climate-linked pay adjust their supplier-switching strategies to facilitate outsourcing. I focus on offshore suppliers because domestic suppliers face the same legal stringency as the focal firm. Research suggests that country-level characteristics play an important role in influencing local firms' corporate decisions (Ioannou and Serafeim 2012; Dhaliwal et al. 2012; Liang and Renneboog 2017; Darendeli et al. 2021). I start with FactSet Revere database, which covers domestic and international supply chain relationships. For each customer, I find all suppliers each year and their information including ISIN, home country, etc. I focus on newly initiated (terminated) suppliers in each year since they capture firms' efforts to restructure their supply chain.[19]

I use three country-level measures to proxy for the emissions costs of suppliers 1) environmental enforcement, 2) mandatory ESG reporting laws, and 3) the legal origin of civil law. The first measure is the exposure to suppliers' environmental enforcement. I obtain the data published by the World Economic Forum's Travel and Tourism Competitiveness Reports. I take the index of "Enforcement of Environmental Regulations" as a measure of the environmental enforcement level of a country-year, with a higher value indicating a higher level of environmental enforcement. To calculate the focal firm's exposure to environmental enforcement from suppliers, I follow Nguyen (2021) and define a firm's exposure to

[19] I construct an indicator variable for each supplier that equals one if the contract with the focal customer is newly initiated (terminated) in the current year and zero otherwise.

enforcement from suppliers as the differences between the enforcement level of the supplier's country and that of the focal firm. I then construct the firm-year level exposure to enforcement from suppliers by taking the mean value of the variables across all suppliers of the focal firm as the following: $ENFORCEEXP_{it} = \frac{\sum_{j=1}^{n} ENFORCE_{i,j,t} - ENFORCE_{it}}{n}$, where *n* is the number of suppliers to firm *i* at year *t*, and *j* is the supplier to firm *i* at year *t*. Next, I capture how firms select their newly initiated suppliers and terminate existing supplier contracts. I calculate the exposure to enforcement from initiated (terminated) suppliers as follows, where *m* is the number of newly initiated (terminated) suppliers to firm *i* in year *t*.[20]

$$InitENFORCE_{it}/TrmtENFORCE_{it} = \frac{\sum_{j=1}^{m} ENFORCE_{i,j,t} - ENFORCE_{it}}{m}$$

My second measure for emissions costs is related to ESG reporting laws. Prior literature finds that country-level ESG activities are positively associated with the mandatory ESG reporting laws (e.g., Chen et al. 2018; Christensen et al. 2021; Downar et al. 2021). The more actively a country is engaged in ESG activities, the more costly it is for a focal firm to outsource emissions to that country. I combine the dataset provided by Krueger et al. (2021) and Christensen et al. (2021) on the ESG mandatory disclosure laws and obtain 32 countries mandating ESG reporting until the end of my sample, as shown in Online Appendix OA3. I define mandatory ESG reporting as a binding requirement by a legal or financial institution (e. g., government or stock exchange) that mandates certain companies to publish an ESG report, which applies to a broad segment of public firms or large private firms.[21] In this context, I define a country-year level indicator variable $ESGLAW_{j,t}$ which takes the value of one if the country-year has mandatory ESG reporting law. I then construct the firm-year level exposure

[20] Initiated suppliers are those whose contracts with the focal firm start in the current year. Terminated suppliers are those whose contracts with the focal firm end in the current year.

[21] A few countries are excluded from my definition because of the limited scope of their ESG reporting regulations. For instance, the ESG law in Sweden only applies to state-owned enterprises. The requirements in Israel and Nigeria applied to banks, and in Qatar, they applied to oil, energy, and transportation firms.

to ESG laws from suppliers by taking the mean value of the variables across all suppliers of the focal firm as follows: $ESGLAWEXP_{it} = \frac{\sum_{j=1}^{n} ESGLAW_{i,j,t}}{n}$, where *n* is the number of suppliers to firm *i* in year *t*, and *j* is the supplier to firm *i* in year *t*. Similarly, I calculate the exposure to ESG laws of initiated (terminated) suppliers as follows, where m is the number of newly initiated (terminated) suppliers to firm *i* in year *t*.

$$InitESGLAW_{it}/TrmtESGLAW_{it} = \frac{\sum_{j=1}^{m} ESGLAW_{i,j,t}}{m}$$

My third measure is the percentage of suppliers located in civil law countries. Liang and Renneboog (2017) find that countries with civil law origins have higher CSR ratings and more actively engage in CSR activities, which makes it harder to outsource emissions to such countries. Similarly, I construct the following measure: $CIVILLAWEXP_{it} = \frac{\sum_{j=1}^{n} CIVILLAW_{i,j,t}}{n}$, where *n* is the number of suppliers to firm *i* in year *t*, and *j* is the supplier to firm *i* in year *t*. *CIVILLAW* is an indicator variable that equals one if the country in which the firm is headquartered has the legal origin of civil law, and zero otherwise.[22] I calculate the exposure to the civil law of initiated (terminated) suppliers as follows, where m is the number of initiated (terminated) suppliers to firm *i* in year *t*.

$$InitCIVIL_{it}/TrmtCIVIL_{it} = \frac{\sum_{j=1}^{m} CIVILLAW_{i,j,t}}{m}$$

Then I estimate the equation (3). The dependent variable $Y_{i,t}$ represents the environmental enforcement exposure to initiated/terminated suppliers (*InitENFORCE/TrmtENFORCE*), the percentage of initiated/terminated suppliers who have mandatory ESG reporting requirements (*InitESGLAW/TrmtESGLAW*), and the percentage of initiated/terminated suppliers with legal origins of civil law (*InitCIVIL/TrmtCIVIL*), respectively. Apart from all control variables in equation (2), I also control for a set of variables that could impact the supply chain, including

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[22] I classify current and former socialist law countries into their pre-socialist legal origin (either French civil law or German law).

the number of suppliers, and firms' exposure to suppliers in the previous year. I include both GIC industry and year fixed effects.

$$Y_{i,t} = ClimateLink_{i,t-1} + Controls + FEs + \epsilon_{it} \quad (3)$$

Table 7 Panel A reports the Probit-2SLS regression results of equation (3). In Column (1) to (3), I find that firms with climate-linked pay significantly reduce their exposure to newly initiated suppliers from regions with higher environmental enforcement, regions with mandatory ESG reporting laws, or regions with origins of Civil laws. Collectively, it shows that firms initiate fewer contracts with suppliers with higher costs of emissions outsourcing. Comparatively, I find positive coefficients on *ClimateLink* across Column (4) to (6), suggesting that firms with climate-linked pay also tend to terminate contracts with suppliers with higher costs of emissions outsourcing. Taken together, climate-linked pay exerts real effects on firms' decisions to switch suppliers.

To strengthen the identification of my test on the mechanism, I exploit the exogenous shock on ESG reporting laws in **Table 7 Panel B**. Following prior literature (e.g., Ioannou and Serafeim 2017), I select two sets of countries where ESG reporting laws were mandated during my sample period. One set of countries, including China, which mandated ESG reporting in 2008, and India, which mandated ESG reporting in 2013, had very low levels of ESG reporting prior to their respective regulations.[23] The other set of countries, including Denmark, started mandatory ESG reporting in 2009, and South Africa, which mandated ESG disclosure in 2010 and, already had widespread sustainability reporting prior to the regulations. These facts imply that I would only observe an exogenous increase in the costs of outsourcing emissions to China

[23] Ioannoue and Serafeim 2017 conduct case studies for China, Demark, Malaysia and South Africa. I replace Malaysia with India in my analyses since I do not have sufficient pre-regulation observations for Malaysia which mandated the ESG reporting regulation in 2007. Alternatively, India has been documented in prior literature to experience exogenous shocks in ESG reporting around its mandatory ESG regulation in 2013. (e.g., Rajgopal and Tantri 2022)

and India when the mandatory ESG reporting laws were enacted in these two countries, respectively. Accordingly, I apply a DiD method using the following specification.

$$\%InitSUPPLIER_{i,j,t} = ClimateLink_{i,t-1} + POSTESG_j + ClimateLink_{i,t-1} \times POSTESG_j + Controls + FEs + \epsilon_{it} \quad (4)$$

$\%InitSUPPLIER_{i,j,t}$ is the percentage of initiated suppliers from country *j* (i.e., China, India, Denmark and South Africa) of firm *i* in year *t*, and $POSTESG_j$ is an indicator variable for the years after the mandatory ESG reporting is adopted in country *j*. All control variables discussed in equation (3) are included. I also control for firm and year fixed effects.

Table 7 Panel B reports the regression results of equation (4). I find negative and significant coefficients on the interaction between *ClimateLink* and *POSTESG* for China and India, but insignificant coefficients for Denmark and South Africa. Overall, these results suggest that in the presence of climate-linked pay, firms reduce the percentage of newly initiated suppliers from countries where the costs of emissions outsourcing become exogenously high.

Next, I validate the supplier switching channel by directly examining whether the association between climate-linked pay and GHG emissions outsourcing is moderated by supplier switching costs. Klemperer (1987) identifies three distinct components of switching costs: (1) differential transaction costs (e.g., incremental shipping and handling charges of a competitor), (2) learning costs related to substituting suppliers' policies and practices, and (3) the unique-to-the-supplier benefits forgone by a customer who switches. Accordingly, I use two measurements to capture supplier switching costs. The first proxy is the supply network complexity that arises from the level of inter-connectedness among suppliers in a focal firm's network (Choi and Krause 2006). A greater number of shared linkages within a focal firm's supply network facilitates upstream collaboration and information sharing, which can in turn, enhance information flow and knowledge spillovers to the focal firm, leading to lower learning costs related to substituting suppliers (Phelps 2010). Hence, I construct the supply network complexity as the following:

$$Complexity_{it} = \frac{\sum\sum x_{jk,it}}{n_{it}(n_{it}-1)} \quad i \neq j \neq k$$

where $x_{jk,it} = 1$ if a supplier-customer relationship exists between supplier j and k who are direct suppliers to focal firm i in year t, and n_{it} is the total number of firm i's direct suppliers in year t. *Complexity* takes a value from 0 to 1 with a higher value indicating a higher level of inter-connectedness between suppliers of the focal firm, therefore representing a lower level of supplier switching costs.

The second proxy for supplier switching costs is the duration of supplier contracts. Prior studies find that long-term relationships between a firm and its supply chain partners facilitate trust, which reduces the concerns about opportunistic behavior by counterparts (Banerjee and Duflo 2000). For each focal firm-year, I compute a weighted average of the contract duration based on the net sales of each supplier. The longer the weighted average duration of supplier contracts, the greater the benefits that the focal firm needs to forgo when switching suppliers. Hence, a shorter weighted average duration of supplier contracts implies lower switching costs.

Table 7 Panel C reports the Probit-2SLS regression results on the subsamples split by the firm median of switching costs. I find significant and positive coefficients on *ClimateLink* among firms with a higher level of supply network complexity in Column (1) to (3). Similarly, the coefficients on *ClimateLink* are significantly positive in the subsamples with lower contract duration in Column (10) to (12), while the same coefficients are mostly insignificant among the firms with higher contract duration in Column (4) to (6). Collectively, these results suggest that the relationships between *ClimateLink* and the Scope 3 emissions are concentrated in firms with lower supplier switching costs. This evidence further corroborates my main findings and validates the channel of supplier switching, as outsourcing emissions via supplier switching remains a cost-relevant operational decision for firms that use climate-linked pay.[24] [25]

5. Robustness and Additional Tests

5.1 CEO Compensation and GHG Emissions

In this section, I validate the underlying assumption in my study that managers' attention is drawn to Scope 1 emissions, rather than Scope 3 emissions when using climate-linked pay. I test the relationship between the level of CEO cash compensation and GHG emissions. Following Chhaochharia and Grinstein (2009), I estimate the following specification:

$$Log(COMPENSATION) = SCOPE1\% + SCOPE3\% + Controls + \ FEs + \epsilon_{it} \qquad (5)$$

I include financial performance, firm size, leverage, book-to-market ratio, growth rate, board independence, institutional ownership, ESG score, CEO tenure and CEO duality as the control variables. The variables of interest are *SCOPE1%* and *SCOPE3%*, with *SCOPE2%* omitted as the reference.

Table 8 reports the results for equation (5). In Column (1), the coefficient on Scope 1 emissions is significantly negative, suggesting that CEOs in firms with a lower proportion of Scope 1 emissions can receive significantly higher cash compensation. In terms of economic significance, one unit increase in $SCOPE1\%$ leads to a 9.8 percent decrease in CEO cash compensation. Next, I test equation (5) in subsamples with and without climate-linked pay and

[24] To further examine the effect of supply chain shocks on the association between emission outsourcing and climate-linked pay, I also introduce supply chain risk and supply chain sentiment by using textual analysis of earnings call transcripts. I extract 91,582 quarterly earnings conference call transcripts from 2006 to 2020 from Refinitiv. I employ two lists of words – related to supply chain (Erashin et al. 2022) and risks (Hassan et al. 2019) respectively. For each transcript, I construct supply chain risk by calculating the proportion of its discussion related to supply chain risks which is the conditional frequency of supply chain-related words provided that they appear within a 10-word distance of any risk-related keywords. I also construct supply chain sentiment by conditioning on the proximity to positive and negative words, identified from Loughran and McDonald's (2011) dictionary of words related to sentiment in financial texts.

[25] Online Appendix Table OA6 presents the results. Consistent with prior findings that firms outsource in reaction to heightened supply chain shocks, the associations between climate-linked pay and Scope 3 emissions are more pronounced for firms with higher supply chain risk and less positive supply chain sentiment.

report the results in Column (2) and (3). I find that this finding only applies to firms using climate-linked pay. Across all three specifications, the percentage of Scope 3 emissions are insignificant to CEO cash compensation. These results further support my main assumptions that firms have greater intentions to reduce their direct emissions rather than upstream emissions from their supply chain.[26]

5.2 First-time Adoption of Climate-linked Pay

As a further step to sharpen identification, I repeat the previous analysis focusing on firms adopting climate-linked pay for the first time. I define "treatment group" as the firm which adopts climate-linked pay for the first time during the sample period. For each event, I construct a [-6, 6] yearly event window around the first-time adoption and identify a clean control group that has not adopted the climate-linked pay during the event window and belongs to the same 6-digit GIC industry as the treated firms.[27] This stacked dataset overcomes the issues of biased estimates of treatment effects generated by the traditional staggered DID analysis (e.g., Baker et al., 2022; Cengiz et al. 2019). I end up with 185 treated firms and 111 control firms, and estimate the following:

$$SCOPE3_{it} = TREAT \times POST + Controls + FEs + \epsilon_{it} \quad (6)$$

TREAT is an indicator variable that equals one if firm *i* starts to adopt climate-linked pay for the first time during the sample period, and zero otherwise. *POST* is an indicator variable that equals one in the year after the firm adopts climate-linked pay for the first time, and zero otherwise. I include the same control variables as in equation (2). The coefficient on the interaction term $TREAT \times POST$, captures the differential effect between the treatment and

[26] To explore whether the use of climate-linked pay changes managers' allocation of efforts among different tasks or metrics (Holmström 2017), I test the effect of climate-linked pay on pay-for-financial-performance sensitivity and do not find significant results. Additionally, I do not find significant changes in financial performance around the first-time adoption of climate-linked pay. These results suggest that the financial task and climate tasks do not exhibit a perfect substition or complementarity relationship. Results are reported in Online Appendix Table OA7.

[27] My results are robust to using [-5,5], [-4,4], [-3,3] event window.

control groups following firms' initial adoption of climate-linked pay. **Table 9** reports positive and significant coefficients on the interaction terms across all specifications, indicating that firms that adopt the climate-linked pay for the first-time exhibit significantly higher Scope 3 emissions in the subsequent years relative to the control group.

The DiD identification strategy relies on the assumption that, in the absence of the treatment, the treated and control groups would have sustained parallel trends in the outcome variable. Although this assumption cannot be empirically tested, I verify its reasonableness by examining the pre-period trend of treatment effects. Specifically, I replace $TREAT \times POST$ with separate indicator variables with each marking one year over the [-6, 6] period relative to the year of adoption of the climate-linked pay. The coefficient estimates capture the differential outcome variables of the treated firms and control firms in each of the years during [-6, 6]. The coefficients and 95 percent confidence intervals are shown in **Figure 3**. I find no evidence of differential pre-treatment trends. In particular, none of the five coefficient estimates on the pre-treatment years is statistically different from zero, but there is a significant increase thereafter.

5.3 Customers' Use of Climate-linked Pay and Scope 1 Emissions

Next, I examine the effect of customers' use of climate-linked pay on the Scope 1 emissions of such focal firms. If the use of climate-linked pay leads firms to outsource emissions, I would observe an increase in a focal firm's Scope 1 emissions when more customers use climate-linked pay. I estimate the following equation using a subsample of focal firms that do not use climate-linked pay:

$$SCOPE1_{i,t} = Cust\_ClimateLink_{i,t} + Controls + FEs + \epsilon_{it} \qquad (7)$$

The dependent variable is the direct Scope 1 emissions of the focal firm, and the independent variable of interest is the percentage of the firm's customers who use climate-linked pay. I include the same control variables as in equation (2). **Table 10** reports the OLS regression results of equation (7) and I find that *Cust_ClimateLink* is positively associated with firms' Scope 1 emissions. Collectively, these results corroborate my main finding that adopting climate-linked pay leads to emissions outsourcing.

5.4 Emission Outsourcing and Revenue-linked Pay

Next, I test whether other compensation metrics can also lead to emissions outsourcing, specifically the effects of revenue-linked incentives on emissions outsourcing. Prior literature suggests that revenue-linked incentives can lead to overproduction and an increase in outsourcing activities (Fershtman and Judd 1987; Bloomfield 2021). I construct an indicator variable *RevenueLink* that equals one if the firm-year uses revenue-linked incentives, and zero otherwise. I re-estimate equation (2) by replacing *ClimateLink* with *RevenueLink* and **Table 11 Panel A** reports the results of the OLS regression. I do not find a positive relationship between the use of revenue-linked incentives and emissions outsourcing, thus ruling out this alternative explanation. **Table 11 Panel B** reports the Probit-2SLS regressions results. Similarly, I use the percentage of firms that use revenue-linked incentives served by the same compensation consultant as the focal firm, and the percentage of firms that use revenue-linked incentives located in the same state as the focal firm, as two instrumental variables to address the selection bias of *RevenueLink.* The results are qualitatively similar to those of OLS regressions.

5.5 Alternative Measure for GHG Emissions Outsourcing

Finally, I include all indirect GHG emissions, including Scope 2 and Scope 3 emissions as an alternative measure for emissions outsourcing. I construct *UPSTREAM* as the total upstream emissions of firms by aggregating Scope 2 emissions and upstream Scope 3 emissions. **Table 12** presents the regression results of my main tests. **Table 12 Panel A** reports significant and positive coefficients on *ClimateLink* across all forms of upstream emissions. Similarly, **Table 12 Panel B** shows that climate-linked pay is significantly and negatively associated with Scope 1 emissions. Finally, **Table 12 Panel C** shows that firms which adopt the climate-linked pay for the first-time exhibit significantly higher upstream emissions in the subsequent years relative to the control group. Collectively, my main findings are robust to this new measure of emissions outsourcing.

6. Conclusion

Climate change has become a global challenge. Over the past decade, an increasing corporate response is to align executive compensation with ESG performance. While prior literature examines the within-firm consequences of nonfinancial metrics in executives' compensation, there is little evidence on how climate-linked metrics in executives' compensation impact the supply chain. This study finds that firms with better corporate governance, better financial performance, and lower growth opportunities are more likely to link executives' compensation to climate-related performance. The use of climate-linked pay leads firms to outsource their GHG emissions to the supply chain, measured as Scope 3 emissions. This effect is primarily driven by firms with higher climate-related pressure, higher bargaining power over suppliers, lower external monitoring, and lower supplier switching costs. To test one possible channel through which firms outsource their emissions, I examine firms' supplier switching decisions. I exploit the country-level characteristics of suppliers and find evidence that firms with climate-linked pay initiate (terminate) fewer (more) contracts with suppliers from regions facing higher costs of emissions, proxied by higher environmental enforcement, mandatory ESG reporting regulations, and legal origins of civil law. This study suggests that the effective use of climate-related metrics in executive compensation requires more careful design and greater board oversight to minimize executives' gaming of emissions allocations along the supply chain.

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Figure 1. Percentage of firms linking executive incentives to climate targets

Figure 1 presents the use of climate-linked pay among US firms from 2006 to 2020 by year. The line depicts the percentage of the use of climate-linked pay among US firms from 2006 to 2020. The bar depicts the total number of unique firms in each year.

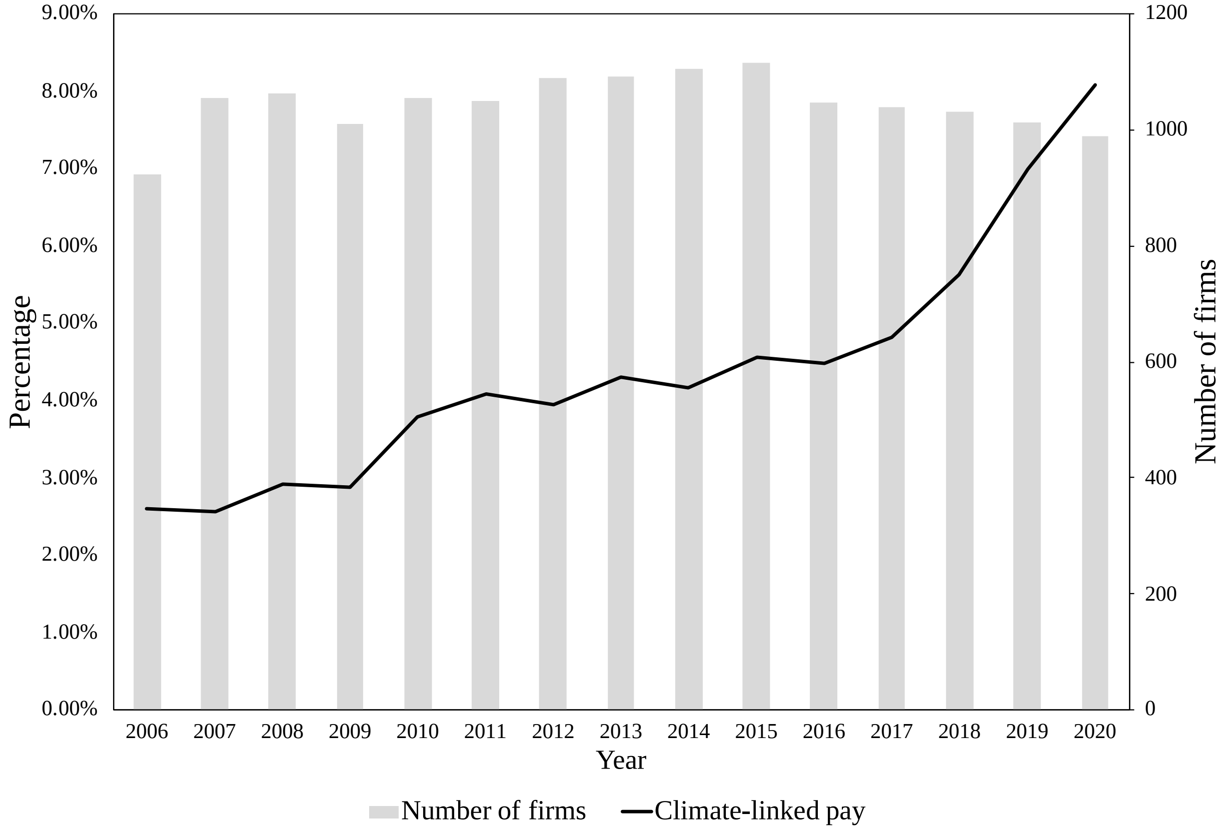
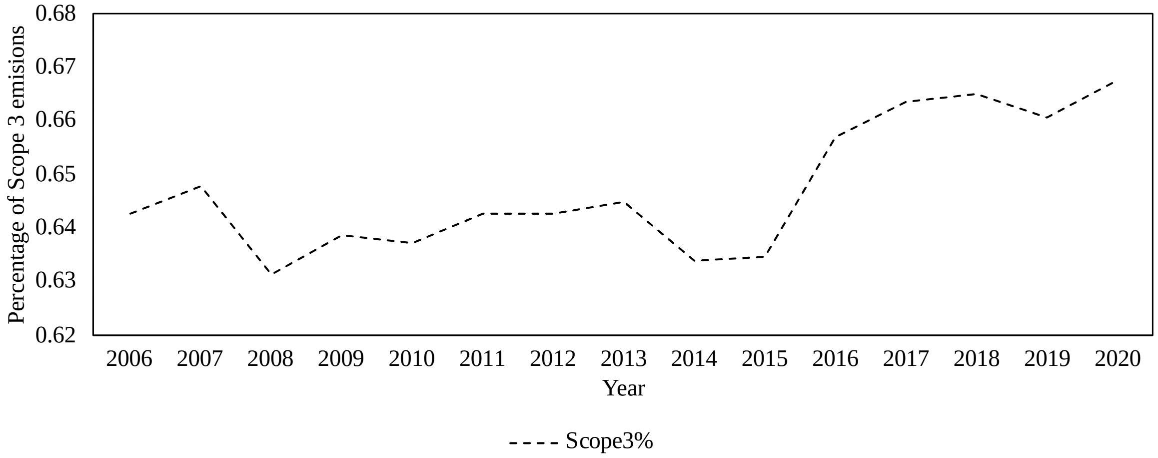
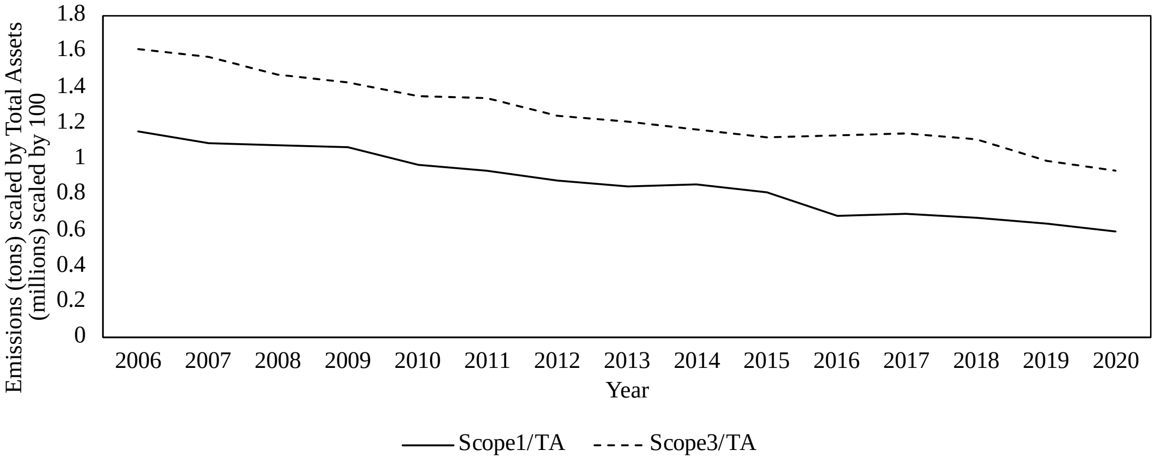


Figure 2. Time trend of GHG emissions

Figure 2 depicts the firm's Scope 1 and Scope 3 emissions by year. Scope 3 emissions take the forms of Scope 3 emissions divided by total emissions, by total assets, and by total sales respectively.





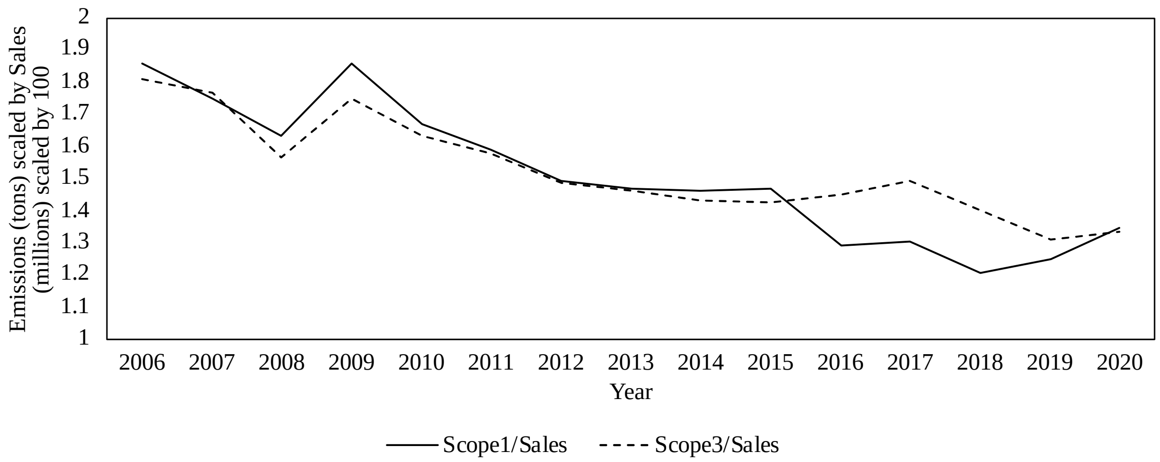


Figure 3. First-time adoption of climate-linked pay and emissions

Figure 3 depicts the firm's Scope 3 emissions around the first-time adoption of climate-linked pay. I re-estimate equation (5) by replacing the interaction term with separate indicator variables that mark the years to the year of the first-time adoption of climate-linked pay. The dependent variable is Scope 3 emissions (upstream emissions) scaled by total assets, total sales, and total emissions, respectively. The figure plots the coefficient estimates with a 95% confidence interval.

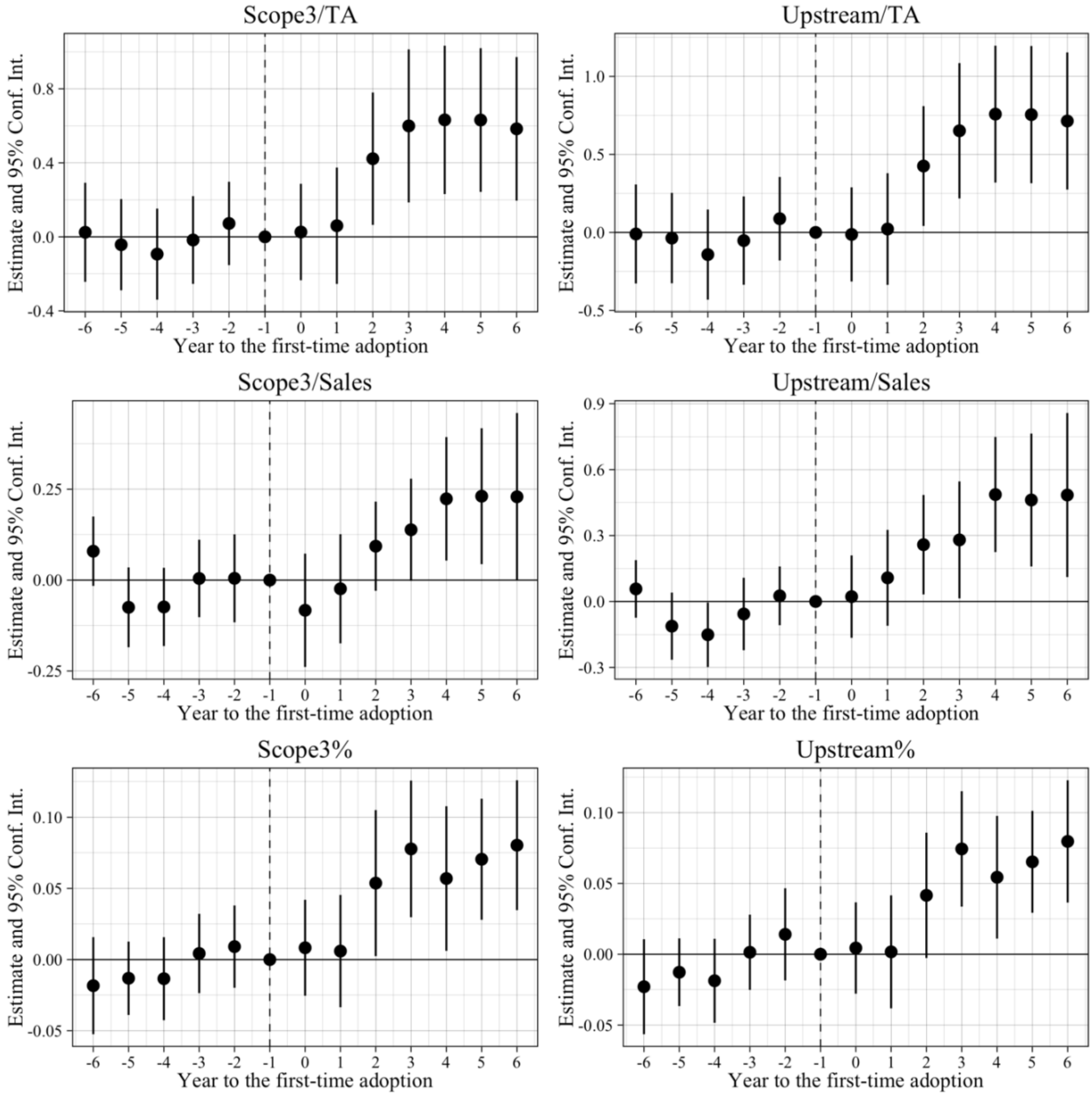


Table 1. Sample selection

This table provides descriptive statistics of the main variables. Panel A reports the sample construction process. Panel B reports the industry distribution of the sample. All variables are defined in Appendix A. All continuous variables are winsorized at 5% and 95%.

Panel A: Sample construction

Observations from 2006 to 2020 in proxy statements	18,011
Less:	
Observations without compensation consultants	1,655
Observations whose headquarters not in U.S.	669
Observations without emissions data	3,445
Observations without executive data	1,114
Observations without governance data	1,944
Observations without financial data	1,854
Sample:	7,330

Panel B: Sample distribution by industry

4-digit GIC	Industry name	# obs	# firms	% *ClimateLink*
1010	Energy	540	68	31.11
1510	Materials	580	61	8.10
2010	Capital Goods	764	78	2.23
2020	Commercial & Professional Services	216	28	0.46
2030	Transportation	204	25	0.98
2510	Automobiles & Components	88	12	0.00
2520	Consumer Durables & Apparel	318	36	1.89
2530	Consumer Services	310	39	4.19
2550	Retailing	493	52	0.00
3010	Food & Staples Retailing	81	8	0.00
3020	Food, Beverage & Tobacco	304	39	0.00
3030	Household & Personal Products	85	9	3.53
3510	Health Care Equipment & Services	531	61	0.19
3520	Pharmaceuticals, Biotechnology & Life Sciences	351	45	0.57
4010	Banks	2	1	0.00
4020	Diversified Financials	214	33	1.40
4030	Insurance	183	25	0.00
4510	Software & Services	489	61	0.20
4520	Technology Hardware & Equipment	409	54	0.24
4530	Semiconductors & Semiconductor Equipment	276	36	3.62
5010	Telecommunication Services	89	13	2.25
5020	Media & Entertainment	189	29	0.00
5510	Utilities	525	49	20.76
6010	Real Estate	89	14	1.12

Table 2. Summary statistics

This table provides the descriptive statistics of the main variables. Panel A reports the summary statistics for the variables. Panel B reports the statistics for subsamples partitioned by climate-linked pay. All variables are defined in Appendix A. All continuous variables are winsorized at 5% and 95%.

Panel A: Descriptive statistics

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
ClimateLink	7,330	0.053	0.224	0.000	0.000	0.000
SCOPE1/TA	7,330	0.979	1.978	0.039	0.152	0.594
SCOPE3/TA	7,330	1.432	1.377	0.390	0.939	2.014
SCOPE1/SALES	7,330	1.747	3.860	0.054	0.176	0.674
SCOPE3/SALES	7,330	1.718	1.343	0.602	1.242	2.587
SCOPE1%	7,330	0.207	0.255	0.039	0.095	0.230
SCOPE3%	7,330	0.649	0.254	0.520	0.738	0.857
TOBINQ	7,330	1.721	1.099	0.931	1.400	2.175
NOISE	7,330	1.391	1.168	0.566	0.967	1.768
ROA	7,330	0.107	0.067	0.061	0.099	0.149
RET	7,330	0.090	0.313	-0.117	0.084	0.276
SIZE	7,330	9.051	1.237	8.114	8.930	9.959
LEV	7,330	0.276	0.177	0.146	0.263	0.383
CASH	7,330	0.131	0.133	0.032	0.085	0.185
PPE	7,330	0.530	0.384	0.200	0.422	0.853
INVEST	7,330	0.045	0.035	0.018	0.035	0.063
INST	7,330	0.794	0.173	0.703	0.830	0.920
STRATEGY	7,330	-0.002	0.009	-0.005	-0.001	0.001
BOARDIND	7,330	0.819	0.092	0.769	0.846	0.900
EXECDIR	7,330	0.292	0.129	0.200	0.250	0.400
SALESGTH	7,330	0.048	0.138	-0.025	0.044	0.111
HHI	7,330	0.074	0.043	0.043	0.057	0.103
CONSULT.PERCT	7,330	3.999	3.545	0.000	3.687	5.618
STATE.PERCT	7,330	3.897	4.285	0.000	2.400	6.400
#SUPPLIERS	7,085	23.646	42.827	1	4	10
ENFORCEEXP	7,040	0.264	0.331	-2.643	0	0.188
ESGLAWEXP	7,085	0.164	0.196	0	0	0.1
CIVILLAWEXP	7,085	0.155	0.181	0	0	0.111

Panel B: Descriptive statistics by climate-linked pay

Statistic	*ClimateLink = 1*	*ClimateLink = 0*	Diff in means
TOBINQ	1.119	1.755	-0.636***
NOISE	1.69	1.375	0.315***
ROA	0.075	0.109	-0.034***
RET	0.063	0.091	-0.029*
SIZE	9.871	9.005	0.866***
LEV	0.308	0.274	0.034***
CASH	0.058	0.135	-0.077***
PPE	0.93	0.507	0.423***
INVEST	0.074	0.043	0.031***
INST	0.737	0.797	-0.060***
STRATEGY	-0.001	-0.002	0.001
BOARDIND	0.851	0.818	0.033***
EXECDIR	0.291	0.292	-0.001
SALESGTH	0.011	0.05	-0.039***
HHI	0.054	0.075	-0.021***
CONSULT.PERCT	7.039	3.829	3.21***
STATE.PERCT	7.705	3.684	4.021***
	387	6,943	

Table 3. Determinants of climate-linked pay

This table reports the Probit regression results of the determinant model of climate-linked pay. The sample includes U.S. firms from 2006 to 2020. The dependent variable is *ClimateLink*, an indicator that equals one on the use of climate-linked pay, and zero otherwise. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of the GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. Standard errors are clustered at the firm level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	Dependent variable:
	ClimateLink
	(1)
$TOBINQ_{t-1}$	-0.391***
	(0.106)
$NOISE_{t-1}$	0.078
	(0.060)
ROA_{t-1}	3.062***
	(1.118)
RET_{t-1}	0.390***
	(0.131)
$SIZE_{t-1}$	0.162**
	(0.065)
LEV_{t-1}	-0.505
	(0.474)
$CASH_{t-1}$	0.412
	(0.933)
$STRATEGY_{t-1}$	2.266
	(7.446)
$INST_{t-1}$	-0.436
	(0.354)
$EXECDIR_{t-1}$	0.352
	(0.446)
$BOARDIND_{t-1}$	0.959*
	(0.552)
$CONSULT.PERCT_{t-1}$	0.073***
	(0.014)
$STATE.PERCT_{t-1}$	0.045***
	(0.014)
Observations	7330
Year FE	Yes
Industry FE	Yes
Pseudo R2	0.436

Table 4. Climate-linked pay and GHG emissions

This table reports the OLS results on the effects of climate-linked pay on GHG emissions. The dependent variable of Column (1) to (3) is the Scope 3 emissions scaled by total assets, the Scope 3 emissions scaled by total sales, and the proportion of Scope 3 emissions, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

		Dependent variable:		
		SCOPE3/TA	*SCOPE3 SALES*	*SCOPE3%*
	Predicted	(1)	(2)	(3)
$\boldsymbol{ClimateLink_{t-1}}$	**(+)**	**0.283*****	**0.176****	**0.019***
		(0.092)	**(0.079)**	**(0.011)**
$SCOPE1/TA$		0.105***		
		(0.014)		
$SCOPE1/Sales$			0.037***	
			(0.011)	
$Log(SCOPE1_{t-1})$		0.130***	0.154***	-0.055***
		(0.011)	(0.016)	(0.003)
$TOBINQ_{t-1}$		-0.031	-0.027*	-0.002
		(0.021)	(0.016)	(0.003)
ROA_{t-1}		3.473***	0.948***	0.402***
		(0.362)	(0.275)	(0.046)
RET_{t-1}		0.039	0.0002	0.006
		(0.051)	(0.036)	(0.007)
$SIZE_{t-1}$		-0.239***	-0.143***	0.043***
		(0.016)	(0.014)	(0.002)
LEV_{t-1}		-0.542***	-0.010	-0.025**
		(0.069)	(0.049)	(0.011)
$CASH_{t-1}$		-0.225***	0.078	0.013
		(0.087)	(0.073)	(0.016)
$INST_{t-1}$		-0.228***	-0.193***	-0.047***
		(0.065)	(0.056)	(0.011)
$BOARDIND_{t-1}$		0.801***	0.010	0.047**
		(0.126)	(0.099)	(0.020)
$EXECDIR_{t-1}$		0.017	0.001	0.013
		(0.085)	(0.075)	(0.013)
$INVEST_{t-1}$		-2.716***	-2.338***	-0.213**
		(0.648)	(0.626)	(0.102)
HHI		0.466	1.613***	0.246***
		(0.576)	(0.556)	(0.083)
$SALESGTH$		0.135	-0.021	-0.003
		(0.096)	(0.070)	(0.014)
PPE_{t-1}		0.082	0.161***	-0.115***
		(0.076)	(0.056)	(0.012)
Observations		7,330	7,330	7,330
Industry, Year FE		Yes	Yes	Yes
Adjusted R2		0.645	0.741	0.782

Table 5. Probit-2SLS tests and GHG emissions

This table reports the Probit-2SLS results on GHG emissions. In Panel A, the dependent variable of Column (1) to (3) is the Scope 3 emissions scaled by total assets, the Scope 3 emissions scaled by total sales, and the proportion of Scope 3 emissions, respectively. Panel B reports the validity test of instrumental variables. In Panel C, the dependent variable of Column (1) to (3) is the scope 1 emissions scaled by total assets, the scope 1 emissions scaled by total sales, and the proportion of scope 1 emissions, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Scope 3 emissions

		Dependent variable:		
		SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*
	Predicted	(1)	(2)	(3)
$\boldsymbol{ClimateLink_{t-1}}$	**(+)**	**0.596*****	**0.670*****	**0.050***
		(0.175)	**(0.213)**	**(0.029)**
		(0.057)	(0.077)	(0.012)
Observations		7,330	7,330	7,330
Controls		Yes	Yes	Yes
Industry, Year FE		Yes	Yes	Yes
Adjusted R2		0.741	0.645	0.782
Weak IV		421.880***	421.880***	421.880***
Hausman test		20.305***	33.174***	3.522*

Panel B: Test of validity of instruments

	Dependent variable:		
	Residuals of Model (1)	Residuals of Model (2)	Residuals of Model (3)
$CONSULT.PERCT_{t-1}$	0.005	0.003	-0.001
	(0.005)	(0.006)	(0.001)
$STATE.PERCT_{t-1}$	-0.005	-0.002	0.001
	(0.006)	(0.007)	(0.001)
$\widehat{ClimateLink}_{t-1}$	0.007	0.0004	0.013
	(0.336)	(0.402)	(0.049)
Observations	7,330	7,330	7,330
Controls	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes
R2	0.003	0.002	0.002
Test of coeff. on IV	F-stat=2.001	F-stat= 0.508	F-stat= 2.926
Test of model R2 (Sargan test)	0.393	3.333	1.738

Panel C: Scope 1 emissions

		Dependent variable:		
		SCOPE1/TA	*SCOPE1/SALES*	*SCOPE1%*
	Predicted	(1)	(2)	(3)
$\boldsymbol{ClimateLink_{t-1}}$	**(−)**	**-0.279**	**-1.252***	**-0.079*****
		(0.249)	**(0.656)**	**(0.030)**
SCOPE3/TA		0.167***		
		(0.023)		
SCOPE3/SALES			0.305***	
			(0.088)	
Observations		7,330	7,330	7,330
Controls		Yes	Yes	Yes
Industry, Year FE		Yes	Yes	Yes
Adjusted R2		0.733	0.748	0.854

Table 6. Cross-sectional analyses

Panel A, B, and C reports the Probit-2SLS regression results for subsamples partitioned by climate pressure, bargaining power, and external monitoring, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: sample split by climate pressure

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3 SALES*	*SCOPE3%*
		High ESG Score			***High Climate Change Exposure***	
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	0.218	0.242	0.031	0.731***	0.800***	0.097***
	(0.288)	(0.269)	(0.036)	(0.212)	(0.262)	(0.033)
Observations	3,508	3,508	3,508	3,545	3,545	3,545
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.678	0.781	0.831	0.681	0.601	0.824
		Low ESG Score			***Low Climate Change Exposure***	
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	0.896***	0.794***	0.065*	0.107	0.112	-0.104
	(0.196)	(0.171)	(0.034)	(0.364)	(0.454)	(0.075)
Observations	3,518	3,518	3,518	3,552	3,552	3,552
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.646	0.727	0.751	0.814	0.728	0.654
	(1) - (7)	**(2) - (8)**	**(3) - (9)**	**(4) - (10)**	**(5) - (11)**	**(6) - (12)**
Chi-squared	2.71*	3.29*	0.53	1.71	2.48	7.89***

Table 6. Cross-sectional analyses (continued)

Panel B: sample split by bargaining power

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*
		High #Supplier			***High Supplier Concentration***	
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	0.329*	0.727***	0.058**	0.305	-0.249	-0.016
	(0.197)	(0.198)	(0.028)	(0.434)	(0.327)	(0.054)
Observations	3,257	3,257	3,257	3,257	3,257	3,257
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.656	0.755	0.843	0.682	0.761	0.743
		Low #Supplier			***Low Supplier Concentration***	
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	0.175	-0.122	-0.030	0.573**	0.980***	0.052*
	(0.207)	(0.189)	(0.033)	(0.236)	(0.198)	(0.030)
Observations	3,266	3,266	3,266	3,266	3,266	3,266
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.712	0.772	0.749	0.650	0.755	0.829
	(1) - (7)	**(2) - (8)**	**(3) - (9)**	**(4) - (10)**	**(5) - (11)**	**(6) - (12)**
Chi-squared	0.27	8.65***	3.87**	0.42	11.84***	1.72

Panel C: sample split by external monitoring

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*
		High #Block holders			***High Analyst Coverage***	
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	-0.109	0.164	-0.008	0.374*	0.223	-0.015
	(0.212)	(0.212)	(0.023)	(0.214)	(0.193)	(0.030)
Observations	3,385	3,385	3,385	3,661	3,661	3,661
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.667	0.771	0.839	0.642	0.740	0.779
		Low #Block holders			***Low Analyst Coverage***	
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	1.344***	1.080***	0.139**	0.939***	0.804***	0.106**
	(0.313)	(0.280)	(0.068)	(0.364)	(0.293)	(0.043)
Observations	3,720	3,720	3,720	3,670	3,670	3,670
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.673	0.743	0.759	0.660	0.750	0.800
	(1) - (7)	**(2) - (8)**	**(3) - (9)**	**(4) - (10)**	**(5) - (11)**	**(6) - (12)**
Chiu-squared	2.69*	3.60**	8.19***	19.37***	9.04***	11.59***

Table 7. Test of mechanism: supplier switching decisions

Panel A of Table 7 reports the Probit-2SLS regression results on supplier switching decisions. The dependent variable for Column (1) to (3) is the exposure to the environmental enforcement of newly initiated suppliers, the percentage of newly initiated suppliers from regions with mandatory ESG reporting laws, and the percentage of newly initiated suppliers from regions with civil law as the legal origin, respectively. The dependent variable for Column (4) to (6) is the exposure to the environmental enforcement of terminated suppliers, the percentage of terminated suppliers from regions with mandatory ESG reporting laws, and the percentage of terminated suppliers from regions with civil law as the legal origin, respectively. Panel B of the table reports the DiD regression results on supplier switching decisions from specific countries. The dependent variable for Column (1) to (4) is the percentage of newly initiated suppliers from India, China, Denmark, and South Africa, respectively. *POSTESG* in Column (1) to (4) is an indicator variable that equals one for the year after the ESG reporting law was mandated in India, China, Denmark, and South Africa, respectively. Panel C reports the Probit-2SLS regression results for subsamples split by supplier switching costs. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *#SUPPLIER* is the number of total suppliers. Standard errors are clustered at the industry and year level and presented in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Full sample (Probit-2SLS)

	Dependent variable:					
	InitENFORCE	*InitESGLAW*	*InitCIVIL*	*TrmtENFORCE*	*TrmtESGLAW*	*TrmtCIVIL*
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{ClimateLink_{t-1}}$	**-0.161***** **(0.056)**	**-0.086**** **(0.036)**	**-0.055*** **(0.029)**	**0.020** **(0.044)**	**0.076**** **(0.031)**	**0.008** **(0.027)**
$ENFORCEEXP_{t-1}$	0.378*** (0.059)			0.707*** (0.028)		
$ESGLAWEXP_{t-1}$		0.258*** (0.039)			0.890*** (0.029)	
$CIVILLAWEXP_{t-1}$			0.241*** (0.032)			0.866*** (0.032)
$Log(\#SUPPLIERS)$	0.021** (0.009)	0.007 (0.005)	0.014*** (0.005)	-0.025*** (0.007)	-0.002 (0.004)	-0.016*** (0.004)
Observations	5,762	5,841	5,841	5,576	5,653	5,653
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.222	0.269	0.147	0.423	0.441	0.355
Weak IV	355.378***	354.975***	354.975***	381.298***	377.653***	377.653***
Hausman test	3.180*	2.526	1.629	0.001	3.012*	0.019
Sargan test	3.919	0.221	2.080	3.451	1.250	0.500

Panel B: DiD regression regarding four countries

		Dependent variable:			
		$\%InitSUPPLIER_{i,t}$			
	Predicted	(1)	(2)	(3)	(4)
$\boldsymbol{ClimateLink_{t-1} \times POSTESG_i}$	**(−)**	-0.425** (0.206)	-0.413*** (0.137)	0.059 (0.045)	-0.767 (0.800)
$ClimateLink_{t-1}$		-0.064 (0.221)	0.167 (0.119)	-0.003 (0.031)	0.850 (0.815)
$Log(\#SUPPLIERS)$		0.422*** (0.117)	0.158 (0.100)	-0.0001 (0.034)	0.039* (0.022)
$Country_i$		*India*	*China*	*Denmark*	*South Africa*
Observations		7,375	7,375	7,375	7,375
Controls		Yes	Yes	Yes	Yes
Firm, Year FE		Yes	Yes	Yes	Yes
Adjusted R2		0.124	0.131	-0.025	0.030

Table 7. Test of mechanism: supplier switching decisions (continued)

Panel C: Validation on the mechanism of supplier switching (Probit-2SLS)

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*
	High Supply Network Complexity			***High Contract Duration***		
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	1.033***	1.287***	0.106***	0.340	0.579*	0.024
	(0.336)	(0.221)	(0.039)	(0.387)	(0.342)	(0.049)
Observations	3,102	3,102	3,102	3,079	3,079	3,079
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.655	0.756	0.814	0.660	0.743	0.795
	Low Supply Network Complexity			***Low Contract Duration***		
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	-0.043	-0.106	-0.031	0.727**	0.627**	0.077*
	(0.233)	(0.252)	(0.033)	(0.357)	(0.310)	(0.045)
Observations	3,137	3,137	3,137	3,375	3,375	3,375
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.689	0.751	0.780	0.642	0.736	0.770
	(1) - (7)	**(2) - (8)**	**(3) - (9)**	**(4) - (10)**	**(5) - (11)**	**(6) - (12)**
Chiu-squared	8.70***	17.16***	8.34***	1.01	0.02	1.2

Table 8. CEO Compensation and GHG emissions

This table reports the OLS regression results on CEO compensation. The sample includes U.S. firms from 2006 to 2020. The dependent variable is the natural logarithm of CEO's current compensation, including cash and bonus. $Scope1\%$ is the percentage of Scope 1 emissions out of total GHG emissions. $Scope3\%$ is the percentage of Scope 3 emissions out of total GHG emissions. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *BM* is the book-to-market ratio. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CEO TENURE* is the tenure years of the CEO. *CEO DUALITY* is an indicator variable that equals one if the CEO is the chairman, and zero otherwise. *INST* is the ownership of institutional investors. *ESG SCORE* is the ESG rating of firms. *BOARDIND* is the percentage of independent directors. Standard errors are clustered at the industry and year level and presented in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	Dependent variable:		
	$Log\ (COMPENSATION)$		
	(1)	(2)	(3)
	Full sample	$ClimateLink = 1$	$ClimateLink = 0$
$\boldsymbol{SCOPE1}\%$	**-0.104****	**-0.309****	**-0.081**
	(0.049)	**(0.145)**	**(0.049)**
$\boldsymbol{SCOPE3}\%$	**-0.044**	**-0.249**	**-0.030**
	(0.041)	**(0.158)**	**(0.043)**
$SIZE$	0.134***	0.108***	0.134***
	(0.005)	(0.021)	(0.005)
LEV	0.050*	-0.432***	0.061**
	(0.029)	(0.129)	(0.028)
BM	-0.028	0.044	-0.031
	(0.019)	(0.075)	(0.019)
ROA	0.467***	-0.102	0.528***
	(0.126)	(0.380)	(0.127)
ROA_{t-1}	0.048	0.602*	-0.024
	(0.115)	(0.358)	(0.120)
RET	0.017	-0.077	0.020
	(0.014)	(0.054)	(0.014)
$CEO\ TENURE$	0.005***	0.008**	0.005***
	(0.001)	(0.003)	(0.001)
$CEO\ DUALITY$	0.033***	0.025	0.032***
	(0.008)	(0.029)	(0.009)
$ESG\ SCORE$	0.001***	0.003**	0.001***
	(0.0002)	(0.001)	(0.0002)
$BOARDIND$	-0.046	0.042	-0.044
	(0.045)	(0.242)	(0.046)
$INST$	0.028	0.013	0.022
	(0.023)	(0.088)	(0.024)
$TOBINQ$	-0.038***	0.049	-0.038***
	(0.006)	(0.052)	(0.006)
Observations	7,666	389	7,277
Industry, Year FE	Yes	Yes	Yes
Adjusted R2	0.372	0.327	0.375
Test on the equality of the coefficient of *SCOPE1%* (one-tailed)		1.78*	

Table 9. First-time adoption of climate-linked pay

This table reports the OLS regression results of the first-time adoption of climate-linked pay. The "treatment group" are firms which adopt climate-linked pay for the first time during the sample period. For each event, I construct a [-6, 6] event window around the first-time adoption and identify a clean control group that hasn't adopted the climate-linked pay during the event window and belongs to the same 6-digit GIC industry as the treated firms. The dependent variable in Panel A is the scope 3 emissions scaled by total assets, scaled by total sales, and the proportion of scope 3 emissions, respectively. *TREAT* is an indicator variable that equals one if a firm adopts climate incentives for the first time during the sample period and zero otherwise. *POST* is an indicator variable that equals one in the year after the first-time adoption and zero otherwise. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	Dependent variable:		
	SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*
	(1)	(2)	(3)
$TREAT \times POST$	0.272***	0.134**	0.027***
	(0.069)	(0.060)	(0.010)
Observations	1,658	1,658	1,658
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Adjusted R2	0.872	0.919	0.947

Table 10: Effect of customers' climate-linked pay on scope 1 emissions

This table reports the OLS regression results of customers' climate-linked pay on the focal firm. The sample consists of focal firms that do not use climate-linked pay. The dependent variable for Column (1) to (3) is the scope 1 emissions scaled by total assets, scope 1 emissions by total sales, and the proportion of scope 1 emissions, respectively. *Cust_ClimateLink* is the percentage of customers who incorporates climate performance in executives' incentives. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	Dependent variable:		
	SCOPE1/TA	*SCOPE1/SALES*	*SCOPE1%*
	(1)	(2)	(3)
$\boldsymbol{Cust\_ClimateLink_{t-1}}$	**-0.092**	**0.532***	**0.033****
	(0.133)	**(0.304)**	**(0.016)**
$SCOPE3/TA$	0.040*		
	(0.023)		
$SCOPE3/SALES$		0.225**	
		(0.091)	
$Log(SCOPE1_{t-1})$	0.393***	0.621***	0.051***
	(0.037)	(0.064)	(0.003)
$TOBINQ_{t-1}$	-0.037*	0.040	0.004
	(0.022)	(0.040)	(0.003)
ROA_{t-1}	0.316	-1.636**	-0.229***
	(0.326)	(0.695)	(0.045)
RET_{t-1}	0.048	0.003	-0.007
	(0.054)	(0.103)	(0.005)
$SIZE_{t-1}$	-0.339***	-0.455***	-0.043***
	(0.037)	(0.059)	(0.003)
LEV_{t-1}	0.319***	0.727***	0.025***
	(0.110)	(0.203)	(0.009)
$CASH_{t-1}$	0.566***	1.228***	0.023
	(0.162)	(0.292)	(0.014)
$INST_{t-1}$	-0.231*	0.024	0.017
	(0.120)	(0.251)	(0.013)
$BOARDIND_{t-1}$	0.050	0.225	-0.009
	(0.206)	(0.359)	(0.020)
$EXECDIR_{t-1}$	0.140	-0.313	-0.017
	(0.111)	(0.210)	(0.013)
$INVEST_{t-1}$	-3.270***	-5.266***	-0.113
	(0.915)	(1.840)	(0.112)
HHI	3.127**	0.468	-0.244***
	(1.232)	(1.299)	(0.087)
$SALESGTH$	0.133	-0.303	0.014
	(0.138)	(0.259)	(0.015)
PPE_{t-1}	0.821***	1.432***	0.077***
	(0.131)	(0.245)	(0.012)
Observations	3,865	3,865	3,865
Industry, Year FE	Yes	Yes	Yes
Adjusted R2	0.720	0.740	0.866

Table 11: Revenue-linked pay and GHG emissions

This table reports the OLS and Probit-2SLS regression results on revenue-linked incentives. The dependent variable of Column (1) to (3) is the scope 3 emissions scaled by total assets, the scope 3 emissions scaled by total sales, and the proportion of scope 3 emissions, respectively. *RevenueLink* is an indicator variable that equals one if the firm-year uses revenue metric in incentives. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: OLS model

	Dependent variable:		
	SCOPE3/TA	*SCOPE3/Sales*	*SCOPE3%*
	(1)	(2)	(3)
$\boldsymbol{RevenueLink_{t-1}}$	**-0.034***	**-0.078*****	**-0.002**
	(0.019)	**(0.023)**	**(0.004)**
Observations	7,330	7,330	7,330
Controls	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes
Adjusted R2	0.740	0.644	0.782

Panel B: Probit-2SLS model

	Dependent variable:		
	SCOPE3/TA	*SCOPE3/Sales*	*SCOPE3%*
	(1)	(2)	(3)
$\boldsymbol{RevenueLink_{t-1}}$	**-0.218*****	**-0.175****	**-0.002**
	(0.058)	**(0.073)**	**(0.011)**
Observations	7,330	7,330	7,330
Industry, Year FE	Yes	Yes	Yes
Adjusted R2	0.740	0.644	0.782
Weak IV	270.782***	271.593***	271.634***

Table 12. Alternative measures of GHG emissions

Table 12 reports the Probit-2SLS regression results in Panel A and B, and OLS regression results in Panel C, using alternative measures for GHG emissions. The dependent variable of Column (1) to (3) in Panel A and Panel C is the total upstream emissions scaled by total assets, the total upstream emissions scaled by total sales, and the proportion of total upstream emissions, respectively. The dependent variable of Column (1) to (3) in Panel B is the scope 1 emissions scaled by total assets, scope 1 emissions scaled by total sales, and the proportion of scope 1 emissions, respectively. *TREAT* is an indicator variable that equals one if a firm adopts climate incentives for the first time during the sample period and zero otherwise. *POST* is an indicator variable that equals one in the year after the first-time adoption and zero otherwise. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by the average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous five years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Upstream emissions and climate-linked pay

		Dependent variable:		
		UPSTREAM/TA	*UPSTREAM/SALES*	*UPSTREAM%*
	Predicted	(1)	(2)	(3)
$ClimateLink_{t-1}$	(+)	0.898***	1.005***	0.079***
		(0.210)	(0.245)	(0.030)
Observations		7,330	7,330	7,330
Controls		Yes	Yes	Yes
Industry, Year FE		Yes	Yes	Yes
Adjusted R2		0.753	0.666	0.854

Panel B: Scope 1 emissions and climate-linked pay

		Dependent variable:		
		SCOPE1/TA	*SCOPE1/SALES*	*SCOPE1%*
	Predicted	(1)	(2)	(3)
$ClimateLink_{t-1}$	(−)	-0.348	-1.352**	-0.079***
		(0.251)	(0.668)	(0.030)
Observations		7,330	7,330	7,330
Controls		Yes	Yes	Yes
Industry, Year FE		Yes	Yes	Yes
Adjusted R2		0.735	0.750	0.854

Panel C. First-time adoption of climate-linked pay

	Dependent variable:		
	UPSTREAM /TA	*UPSTREAM/SALES*	*UPSTREAM%*
	(4)	(5)	(6)
$TREAT \times POST$	0.439***	0.134**	0.038***
	(0.095)	(0.060)	(0.011)
Observations	1,658	1,658	1,658
Controls	Yes	Yes	Yes
Firm, Year FE	Yes	Yes	Yes
Adjusted R2	0.847	0.919	0.942

Appendix A. Variable definitions

Variable name	Definition
Emissions:	
SCOPE1/TA	Scope 1 emissions (tons) divided by total assets (millions), scaled by 100
SCOPE3/TA	Upstream Scope 3 emissions (tons) divided by total assets (millions), scaled by 100
SCOPE1/SALES	Scope 1 emissions (tons) divided by total sales (millions), scaled by 100
SCOPE3/SALES	Upstream Scope 3 emissions (tons) divided by total sales (millions), scaled by 100
SCOPE1%	The proportion of Scope 1 emissions out of total emissions
SCOPE3%	The proportion of Scope 3 emissions out of total emissions
UPSTREAM/TA	Scope 2 plus Scope 3 emissions (tons) divided by total assets (millions), scaled by 100
UPSTREAM /SALES	Scope 2 plus Scope 3 emissions (tons) divided by total sales (millions), scaled by 100
UPSTREAM %	The proportion of Scope 2 plus Scope 3 emissions out of total emissions
Firm fundamentals:	
ClimateLink	An indicator variable that equals 1 if the firm-year links executive incentives to climate-related metrics, and 0 otherwise
ROA	EBIT divided by the average total assets
NOISE	The time-series standard deviation of GIC industry-median ROA over the years from year t-4 to year t
RET	Annual stock returns
TOBINQ	Market value of equity plus book value of debt, divided by the average total assets
CASH	Cash equivalents divided by the average total assets
LEV	Total liability divided by the average total assets
BM	Book-to-market ratio
SIZE	Log (Total assets +1)
INST	Ownership of Institutional investors
EXECDIR	Percentage of executives sitting on firm's board
BOARDIND	Number of independent directors/Number of board members
PPE	PP&E divided by the average total assets
SALESGTH	Sales/Lagged Sales – 1
STRATEGY	Industry-adjusted variable by using factor analysis on R&D-to-sales ratio, market-to-book ratio, and employees-to-sales ratio.
HHI	Sum of squared sales for each firm in the same GIC industry
CONSULT.PERCT	The proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives in year t
STATE.PERCT	The proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives in year t
CEO TENURE	Number of years of CEO tenure
CEO DUALITY	An indicator variable that equals 1 if the CEO is also the chairman of the firm, and 0 otherwise
COMPENSATION	Cash and bonus of CEO
#BLOCK HOLDER	The number of institutional owners whose holding exceeds 5% of firm's outstanding shares
ANALYST COVERAGE	The number of analysts following
Supply chain structure:	
ENFORCE	Environmental enforcement index
ESGLAW	An indicator variable that equals one if the country has mandatory ESG reporting law
CIVILLAW	An indicator variable that equals one if the country has a legal origin of civil law.
ENFORCEEXP	Average difference between the environmental enforcement index of suppliers and the focal firm

ESGLAWEXP	Percentage of suppliers from regions with mandatory ESG reporting laws
CIVILLAWEXP	Percentage of suppliers from regions with civil law as the legal origin
%InitSUPPLIER	Percentage of initiated suppliers from China, India, Denmark, and South Africa, respectively
InitENFORCE	Average difference between the environmental enforcement index of initiated suppliers and the focal firm
InitESGEXP	Percentage of initiated suppliers from regions with mandatory ESG reporting laws out of all initiated suppliers
InitCIVIL	Percentage of initiated suppliers from regions with civil law as the legal origin out of all initiated suppliers
TrmtENFORCE	Average difference between the environmental enforcement index of terminated suppliers and the focal firm
TrmtESGEXP	Percentage of terminated suppliers from regions with mandatory ESG reporting laws out of all terminated suppliers
TrmtCIVIL	Percentage of terminated suppliers from regions with civil law as the legal origin out of all terminated suppliers
#SUPPLIERS	Number of suppliers
SUPPLIER CONCENTRATION	The Herfindahl-Hirschman index of supplier sales shares
COMPLEXITY	The number of ties in firm's Tier-1 supply network relative to the total possible number of ties
DURATION	The sales-weighted average contract duration of suppliers
Other variables:	
Cust_ClimateLink	Percentage of customers that use climate-linked pay
ReveuneLink	An indicator variable that equals 1 if the firm-year links executive incentives to sales metrics, and 0 otherwise
Supply Chain Risk	A text-based measure on supply chain risk derived from earnings call transcripts, which is the number of occurrences of supply chain-related bigrams (Erashin et al. 2022) indicating discussion of supply chains within the set of 10 words surrounding a synonym for risk (Hassan et al. 2019) on either side in the earnings calls
Supply Chain Sentiment	A text-based measure on supply chain sentiment derived from earnings call transcripts, which is the number of occurrences of supply chain-related bigrams (Erashin et al. 2022) conditioning on the proximity to positive and negative words, identified from Loughran and McDonald's (2011) dictionary of words related to sentiment in financial texts

Online Appendix for "Climate-linked Pay and Supply Chain Management"

Appendix OA1. Examples of climate-linked pay in proxy statements

1. Xcel Energy 2006

25% of awarded performance-based restricted stock units plus associated earned dividend equivalents will be settled, and the restricted period will lapse, after the average actual performance results (adjusted for actual megawatt hours) for the three components of an **environmental index** measured as a percentage of target performance meets or exceeds 100%. The environmental index is measured annually at the end of each fiscal year and includes components based on measurement of **emissions of nitrogen oxide, sulfur dioxide and carbon dioxide**.

2. Covanta Holdings Corp 2010

For 2010, we measured the performance of our named executive officers by our satisfaction of a combination of goals relating to improvements in performance with respect to job safety, compliance, and **air emissions**……and specific target goals for safety incidents and environmental reporting and compliance and emissions levels were established. In 2010, we significantly reduced safety incidents (110% of target) and achieved significant compliance improvements and modest **reductions in emissions**.

3. Verizon Communications Inc. 2017

Verizon is one of the few companies in our peer group that includes a sustainability target as one of the performance measures for management employees' short-term incentive compensation awards. We measure our progress by tracking our **carbon intensity** — the amount of carbon our business emits divided by the terabytes of data we transport over our networks. Our current goal is to reduce our carbon intensity by 50% over the 2016 baseline by 2025, even as we grow our business.

4. Chevron Corp 2020

The Management Compensation Committee assesses and approves the incorporation of **greenhouse gas**–related performance measures into the scorecard that affects the compensation of management and most employees. Weight of 15% is placed on Health, environmental and safely, including personal safety, process safety and environmental, and **greenhouse gas management** – on track to achieve flaring and **methane intensity reductions.**

5. Hudson Pacific Properties Inc. 2020

Performance Units may be earned between 50% and 200% of target based on Net Debt to Gross Asset Value (30%), Leasing Volume (30%), LEED Certification (10%), **Carbon Neutrality** (10%) and G&A to Gross Asset Value (20%) based on performance as of December 31, 2020.

6. Kosmos Energy Ltd. 2020

Entered into an agreement with Shell Energy North America accessing carbon credits from two leading reforestation projects in Ghana and the United States; set goal to be **carbon neutral for Scope 1 and Scope 2 emissions** by 2030 or sooner.

Appendix OA2. Climate-linked keywords in proxy statements

Step 1. Start with "E"-related keywords in Flammer et al. (2019) and Ikram et al. (2019).

- **Flammer et al. (2019):** energy efficiency, environmental compliance, environmental goals, environmental performance, environmental projects, greenhouse gas emissions reductions
- **Ikram et al. (2019):** environment, sustainability

Step 2. Search for the following climate-linked keywords in the CD&A section of proxy statements.

- air, aqua, co2, carbon, ccus, clean, climate, co2, co2e, decarbonization, dioxide, eh&s, ehs, emission, emissions, ems, energy, environment, environmental, environmentally, environmentals, epc, erosion, es&g, esg, footprint, fossil, gas, ghg, green, greenhill, greenhouse, hcei, hsse, leaks, methane, megawatt, megawatts, mwh, nitrogen, oxide, renewable, scope 1, scope 2, scope 3, sediment, sf6, sola, spill, spills, sulfur, sulphur, sustainability, waste, wastewater, water, wildfire, wind

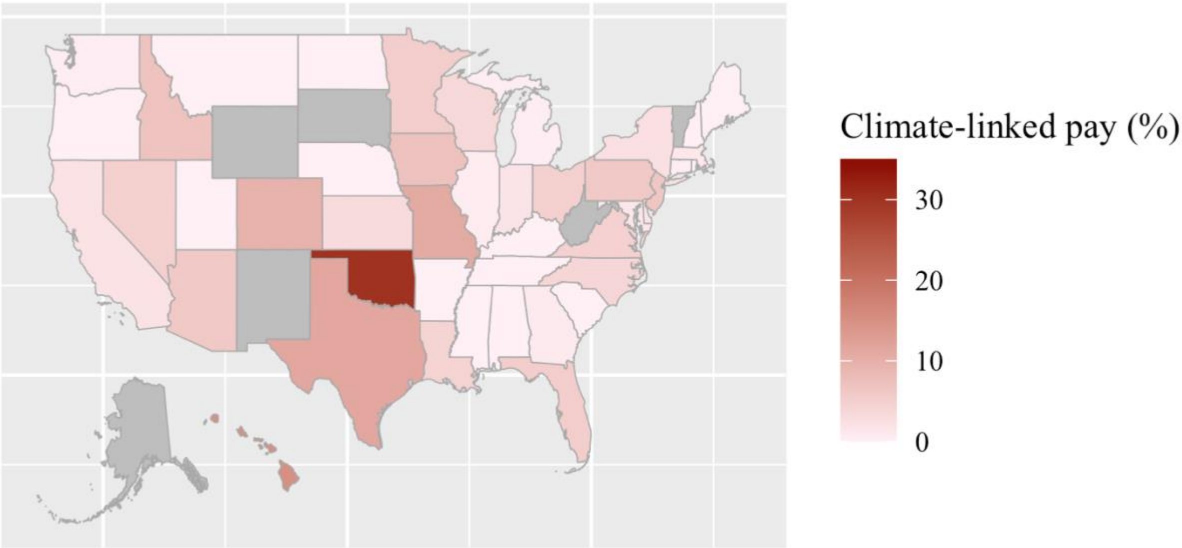
Step 3. Manually check all matches and manually correct unsuccessful matches.

- e.g., remove "audit environment" etc.

Appendix OA3. Mandatory ESG reporting law around the world

Country/Region	Year	Regulation
Argentina	2008	Ley N 2594 de balance de responsabilidad social y ambiental
Australia	2003	Listing Rule 4.10.3, Australian Stock Exchange
Austria	2016	Transposition of EU NFR Directive: Sustainability and Diversity Improvement Act 257/ME
Canada	2004	The TSX Timely Disclosure Policy
Chile	2015	Norma de Caracter General N 385/386
China	2008	Guidelines on Listed Companies' Environmental Information Disclosure
Denmark	2009	The amendment of the Danish Financial Statements Act
Finland	1997	The Finnish Accounting Act
France	2001	New Economic Regulations Act (NRE)
Germany	2016	Transposition of EU NFR Directive: CSR Directive Implementation Act
Greece	2006	Law 3487, 2006
Hong Kong	2015	HKEX Listing Rules Disclosure of Financial Information
Hungary	2016	Transposition of EU NFR Directive: Amendments to Accounting Act C of 2000
India	2013	The Companies Act Section 134(3)
Indonesia	2012	Rule No.KEP-431/BL/2012
Ireland	2016	Transposition of EU NFR Directive (1)
Italy	2016	Transposition of EU NFR Directive: legislative Decree 30 December 2016, n.254
Malaysia	2007	Main Markets listing requirements CSR description
Norway	2013	Act amending the Norwegian Accounting Act
Pakistan	2009	Companies (Corporate Social Responsibility) general order
Peru	2016	Resolucion SMV No 033-2015-SMV/01
Philippines	2011	Corporate Social Responsibility Act, 2011
Poland	2016	Transposition of EU NFR Directive: Amendments to the Accounting Act
Portugal	2010	The Financial Reporting Accounting Standard n 26
Singapore	2016	SGX0ST Listing Rules Practice Note 7.6 Amendments to sustainability reporting guide
Slovenia	2015	Transposition of EU NFR Directive: Amendment to act No. 431/2002 Coll. On Accounting
South Africa	2010	Johannesburg Stock Exchange Listing Requirement 2010
Spain	2012	Spanish Sustainable Economy Law (revision of 2011)
Taiwan	2014	Rules Governing the Preparation and Filing of CSR Reports by TWSE Listed Companies
The Netherlands	2016	Transposition of EU NFR Directive
Turkey	2014	GHG Monitoring Regulation/Communique on corporate governance principles
United Kingdom	2013	The companies Act 2006 Regulations 2013

Figure OA1. Distribution of Climate-linked pay and Emission Outsourcing by State



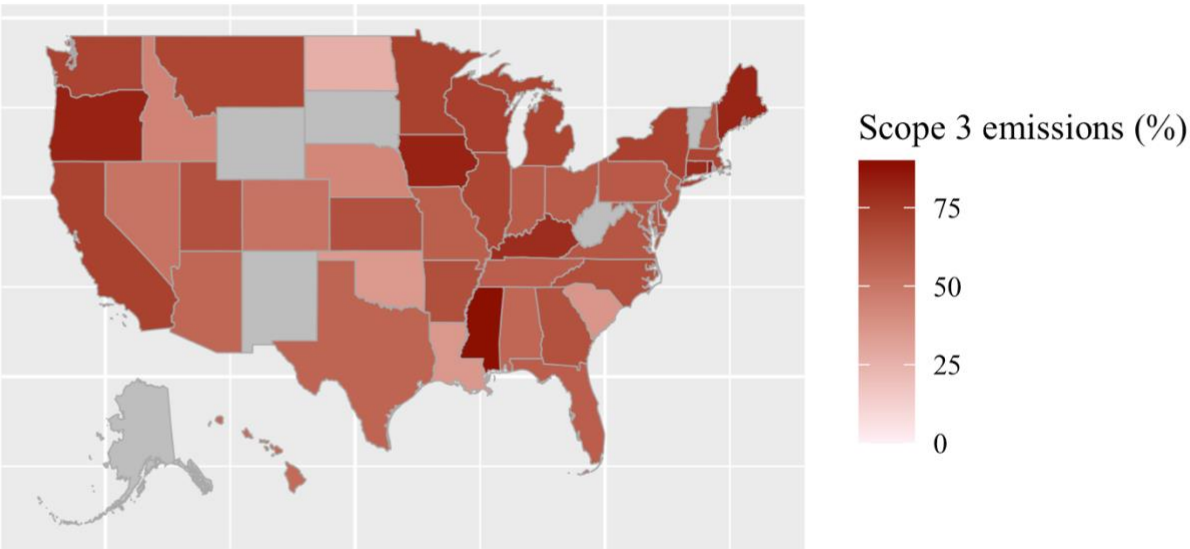


Table OA1. Alternative sample period

This table reports the Probit-2SLS results for the subsample period. Panel A includes observations from 2006-2015, and Panel B includes observations from 2016-2020. The dependent variable of Column (1) to (6) in Panel A and B is Scope 3 emissions scaled by total assets, by total sales, and by total emissions, and the total upstream emissions scaled by total assets, by total sales, and by total emissions, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Sample from 2006 to 2015

	Dependent variable:					
	SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*	*UPSTREAM/TA*	*UPSTREAM/SALES*	*UPSTREAM%*
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{ClimateLink_{t-1}}$	0.376	0.934***	0.087*	0.365*	1.026***	0.096**
	(0.233)	(0.338)	(0.045)	(0.219)	(0.360)	(0.041)
Sample	2006-2015	2006-2015	2006-2015	2006-2015	2006-2015	2006-2015
Observations	4,410	4,410	4,410	4,410	4,410	4,410
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.739	0.648	0.789	0.754	0.674	0.857

Panel B: Sample from 2016 to 2020

	Dependent variable:					
	SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*	*UPSTREAM/TA*	*UPSTREAM/SALES*	*UPSTREAM%*
	(1)	(2)	(3)	(4)	(5)	(6)
$\boldsymbol{ClimateLink_{t-1}}$	1.425***	0.878*	0.036	2.004***	1.382**	0.147**
	(0.466)	(0.516)	(0.067)	(0.526)	(0.614)	(0.068)
Sample	2016-2020	2016-2020	2016-2020	2016-2020	2016-2020	2016-2020
Observations	2,920	2,920	2,920	2,920	2,920	2,920
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.752	0.649	0.780	0.758	0.661	0.856

Table OA2. PSM within emission-intensive industries

This table reports the PSM results for firms in emissions-intensive industries only, namely, mining, manufacturing, and utilities. Panel A reports the covariate balance results after employing a PSM matching with replacement and a calliper of 0.01. Panel B reports the OLS results using the matched sample. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Covariant balance

Variable	$ClimateLink = 1$	$ClimateLink = 0$	**Diff**	**t-stat**
Outcome variables:				
SCOPE3/TA	1.626	1.380	0.246	1.888**
SCOPE3/SALES	2.524	2.366	0.158	1.369
SCOPE3%	0.352	0.360	-0.008	0.315
Control variables:				
ROA_{t-1}	0.075	0.074	0.001	0.213
RET_{t-1}	0.069	0.058	0.011	0.411
$CASH_{t-1}$	0.058	0.065	-0.008	-0.975
PPE_{t-1}	0.919	0.888	0.031	1.070
$TOBINQ_{t-1}$	1.143	1.148	-0.005	-0.102
$Log(SCOPE1_{t-1})$	7.182	7.114	0.068	0.990
LEV_{t-1}	0.310	0.310	-0.0001	-0.013
$SIZE_{t-1}$	9.738	9.592	0.146	1.507
$INVEST_{t-1}$	0.072	0.069	0.003	0.929
$SALEGTH$	0.021	0.025	-0.004	-0.274
HHI	0.056	0.056	-0.0005	-0.161
$BOARDIND_{t-1}$	0.848	0.842	0.005	0.723
$INST_{t-1}$	0.737	0.746	-0.009	-0.627
$STRATEGY_{t-1}$	-0.002	-0.002	-0.0001	-0.194
$EXECDIR_{t-1}$	0.296	0.282	0.014	1.247
$EarningsNoise_{t-1}$	1.320	1.413	-0.093	-0.828

Panel B: OLS regressions using the matched sample

	Dependent variable:		
	SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*
	(1)	*(2)*	*(3)*
$ClimateLink$	0.253***	0.190***	0.012
	(0.092)	(0.071)	(0.012)
Observations	511	511	511
Controls	Yes	Yes	Yes
Year, Industry FE	Yes	Yes	Yes
Adjusted R2	0.627	0.603	0.776

Table OA3. Determinants for climate-linked pay

This table reports the Probit regression results of the determinant model of climate-linked pay. The sample includes U.S. firms from 2006 to 2020. The dependent variable is *ClimateLink*, an indicator that equals one on the use of climate-linked pay, and zero otherwise. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. Standard errors are clustered at the industry and year level and presented in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

		Dependent variable:	
		ClimateLink	
	(1)	(2)	(3)
$TOBINQ_{t-1}$	-0.348***	-0.373***	-0.390***
	(0.102)	(0.104)	(0.105)
$SCOPE1/TA$	0.028		
	(0.034)		
$SCOPE3/TA$	0.078		
	(0.059)		
$SCOPE1/SALES$		0.007	
		(0.018)	
$SCOPE3/SALES$		0.061	
		(0.060)	
$SCOPE1\%$			0.235
			(0.381)
$NOISE_{t-1}$	0.081	0.078	0.079
	(0.059)	(0.059)	(0.059)
ROA_{t-1}	2.434**	2.871***	3.217***
	(1.021)	(1.063)	(1.067)
RET_{t-1}	0.354***	0.383***	0.395***
	(0.126)	(0.128)	(0.130)
$SIZE_{t-1}$	0.181***	0.165**	0.162**
	(0.065)	(0.065)	(0.065)
LEV_{t-1}	-0.490	-0.543	-0.519
	(0.462)	(0.468)	(0.473)
$CASH_{t-1}$	0.380	0.414	0.452
	(0.959)	(0.934)	(0.919)
$STRATEGY_{t-1}$	2.202	2.201	2.653
	(7.687)	(7.505)	(7.399)
$INST_{t-1}$	-0.336	-0.387	-0.449
	(0.349)	(0.356)	(0.353)
$EXECDIR_{t-1}$	0.354	0.353	0.355
	(0.445)	(0.443)	(0.442)
$BOARDIND_{t-1}$	0.811	0.899*	0.938*
	(0.543)	(0.541)	(0.543)
$CONSULT.PERCT_{t-1}$	0.072***	0.073***	0.074***
	(0.014)	(0.014)	(0.014)
$STATE.PERCT_{t-1}$	0.044***	0.044***	0.045***
	(0.014)	(0.014)	(0.014)
Observations	7330	7330	7330
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Pseudo R2	0.439	0.437	0.436

Table OA4. Test of IV

This table reports the regression results of scope 3 emissions on instrumental variables and other endogenous variables. The *SCOPE1* is scope 1 emissions scaled by total assets in Column (1), scope 1 emissions scaled by total sales in Column (2), and the natural logarithm of scope 1 emissions in Column (3). All variables are defined in Appendix OA1. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

	Dependent variable:		
	SCOPE3/TA	*SCOPE3/SALES*	*SCOPE3%*
	(1)	(2)	(3)
$CONSULT.PERCT_{t-1}$	0.007	0.008	-0.001
	(0.005)	(0.005)	(0.001)
$STATE.PERCT_{t-1}$	0.001	-0.003	0.001
	(0.007)	(0.006)	(0.001)
$ClimateLink_{t-1}$	0.269*	0.166	0.019
	(0.144)	(0.124)	(0.018)
$SCOPE1/TA$	0.105***		
	(0.033)		
$SCOPE1/SALES$		0.037**	
		(0.019)	
$Log(SCOPE1_{t-1})$	0.130***	0.155***	-0.055***
	(0.024)	(0.025)	(0.005)
$TOBINQ_{t-1}$	-0.031	-0.027	-0.002
	(0.037)	(0.026)	(0.005)
ROA_{t-1}	3.465***	0.935**	0.404***
	(0.523)	(0.365)	(0.067)
RET_{t-1}	0.040	0.001	0.006
	(0.038)	(0.028)	(0.005)
$SIZE_{t-1}$	-0.240***	-0.145***	0.043***
	(0.034)	(0.028)	(0.005)
LEV_{t-1}	-0.549***	-0.018	-0.024
	(0.146)	(0.112)	(0.021)
$CASH_{t-1}$	-0.219	0.081	0.014
	(0.171)	(0.146)	(0.028)
$INST_{t-1}$	-0.233*	-0.197*	-0.047**
	(0.137)	(0.118)	(0.022)
$BoardInd_{t-1}$	0.798***	0.002	0.049
	(0.271)	(0.212)	(0.039)
$EXECDIR_{t-1}$	0.013	-0.001	0.013
	(0.187)	(0.161)	(0.025)
$INVEST_{t-1}$	-2.700**	-2.313***	-0.217
	(1.074)	(0.868)	(0.163)
HHI_t	0.513	1.675**	0.239*
	(0.914)	(0.797)	(0.130)
$SALESGTH_t$	0.137	-0.019	-0.002
	(0.101)	(0.077)	(0.014)
PPE_{t-1}	0.079	0.156	-0.114***
	(0.154)	(0.123)	(0.023)
Observations	7,330	7,330	7,330
Industry, Year FE	Yes	Yes	Yes
Adjusted R2	0.645	0.741	0.783

Table OA5. GHG emissions outsourcing and emission-intensive firms

This table reports the Probit-2SLS regression results for subsamples partitioned by emission-intensive industries, i.e., utilities, mining, construction, and Scope 1 emissions, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3/ SALES*	*SCOPE3%*
	Emission-intensive industries			***High direct emissions***		
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	0.831**	0.582**	0.075*	0.799***	0.451***	0.076***
	(0.338)	(0.281)	(0.042)	(0.208)	(0.165)	(0.027)
Observations	4,713	4,713	4,713	3,660	3,660	3,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.630	0.669	0.842	0.624	0.675	0.821
	Non-emission-intensive industries			***Low direct emissions***		
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	-0.271	-0.188	-0.002	0.024	-0.452	-0.221**
	(0.231)	(0.116)	(0.031)	(0.648)	(0.522)	(0.107)
Observations	2,617	2,617	2,617	3,670	3,670	3,670
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.675	0.658	0.539	0.739	0.808	0.538
	(1) - (4)	**(2) - (5)**	**(3) - (6)**	**(4) - (10)**	**(5) - (11)**	**(6) - (12)**
Chiu-squared	20.13***	19.56***	4.99**	1.50	3.05*	8.66***

Table OA6. GHG emissions outsourcing and supply chain shocks

This table reports the Probit-2SLS regression results for subsamples partitioned by supply chain risk and supply chain sentiment, respectively. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Dependent variable:	*SCOPE3/TA*	*SCOPE3/SALES*	*SCOPE3%*	*SCOPE3/TA*	*SCOPE3/ SALES*	*SCOPE3%*
	High supply chain risk			***More positive supply chain sentiment***		
	(1)	(2)	(3)	(4)	(5)	(6)
$ClimateLink_{t-1}$	0.937**	0.937***	0.063	0.312	0.471	0.017
	(0.374)	(0.280)	(0.048)	(0.358)	(0.314)	(0.050)
Observations	3,558	3,558	3,558	3,558	3,558	3,558
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year, Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.650	0.746	0.774	0.635	0.741	0.751
	Low supply chain risk			***Less positive supply chain sentiment***		
	(7)	(8)	(9)	(10)	(11)	(12)
$ClimateLink_{t-1}$	0.238	0.199	0.026	0.836***	0.622***	0.062**
	(0.226)	(0.248)	(0.032)	(0.261)	(0.230)	(0.031)
Observations	3,563	3,563	3,563	3,563	3,563	3,563
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry, Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R2	0.649	0.751	0.803	0.644	0.747	0.809

Table OA7. Financial performance and climate-linked pay

Panel A reports the effect of climate-linked pay on pay-for-performance sensitivity. Panel B reports the Probit-2SLS results of the effects of climate-linked pay on financial performance. Panel C reports the change in financial performance around the first-time adoption of climate-linked pay. *TREAT* is an indicator variable that equals one if a firm adopts climate incentives for the first time during the sample period and zero otherwise. *POST* is an indicator variable that equals one in the year after the first-time adoption and zero otherwise. *TOBINQ* is the market value of equity plus the book value of debt, divided by average total assets. *ROA* is EBIT divided by average total assets. *NOISE* is the time-series standard deviation of GIC industry-median ROA over the previous four years. *RET* is the annual stock return. *SIZE* is the natural logarithm of total assets. *LEV* is total liability divided by average total assets. *CASH* is cash equivalents divided by average total assets. *STRATEGY* is an industry-adjusted variable by using factor analysis on R&D to sales ratio, market-to-book ratio, and employee-to-sales ratio. *INST* is the ownership of institutional investors. *EXECDIR* is the percentage of executives sitting on firms' boards. *BOARDIND* is the percentage of independent directors. *CONSULT.PERCT* is the proportion of client firms served by the same compensation consultant of the firm that uses climate-linked metrics in their executive incentives. *STATE.PERCT* is the proportion of firms whose headquarters are located in the same state as the firm that uses climate-linked metrics in their executive incentives. *HHI* is the sum of squared sales for each firm in the same GIC industry. *SALESGTH* is the growth rate of sales. *PPE* is property, plant and equipment divided by average total assets. Standard errors are clustered at the industry and year level and presented in parentheses. ∗∗∗, ∗∗, and ∗ represent statistical significance at the 1%, 5%, and 10% levels (two-tailed), respectively.

Panel A: Pay-for-performance sensitivity and climate-linked pay

	Dependent variable:
	$Log\ (COMPENSATION)$
	(1)
$ClimateLink_{t-1} \times ROA$	-0.430
	(0.297)
$ClimateLink_{t-1} \times ROA_{t-1}$	0.524*
	(0.273)
$ClimateLink_{t-1} \times RET$	-0.008
	(0.051)
$ClimateLink_{t-1}$	-0.002
	(0.022)
Observations	7,666
Industry, Year FE	Yes
Controls	Yes
Adjusted R2	0.372

Panel B: Financial performance and climate-linked pay

	Dependent variable:	
	ROA	*RET*
	(1)	(2)
$\boldsymbol{ClimateLink_{t-1}}$	**-0.032**	**-0.012**
	(0.076)	**(0.009)**
Observations	7,195	7,195
Industry, Year FE	Yes	Yes
Adjusted R2	0.263	0.800

Panel C: Financial performance and first-time adoption of climate-linked pay

	Dependent variable:			
	ROA	ΔROA	*RET*	ΔRET
	(1)	(2)	(3)	(4)
$TREAT\ \times POST$	0.004	0.004	0.051	0.051
	(0.005)	(0.005)	(0.039)	(0.039)
Observations	1,654	1,654	1,670	1,670
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R2	0.724	0.592	0.413	0.741