The Effect of Customer Demand for Carbon Disclosures Along Supply Chains

Jin Deng
Hong Kong University of Science and Technology
jin.deng@connect.ust.hk

Abstract
This study examines how customer demand for suppliers' carbon disclosures affects suppliers' emissions performance. My analysis utilizes the Carbon Disclosure Project (CDP) Supply Chain program, in which participating customer firms request their suppliers disclose greenhouse gas (GHG) information. I find that compared to benchmark suppliers, treatment suppliers exposed to this program experience a decrease in Scope 1 emissions after their customers join the CDP Supply Chain program. These effects are more pronounced when customers have stronger incentives to monitor emissions performance along supply chains and have greater bargaining power, when suppliers face greater pressure to reduce emissions, and when there is greater information asymmetry between suppliers and customers. Further analyses reveal that treatment suppliers attract more customers and have more customers that are willing to publicly disclose their relationships. Participating customers are more likely to disclose upstream Scope 3 emissions, report a more granular breakdown of these emissions, and utilize more data from suppliers in their measurements. Overall, my findings underscore the role of customer demand for carbon disclosures in shaping sustainable behavior along the supply chain and in Scope 3 emissions reporting.

Keywords: Scope 1 emissions; Scope 3 emissions; supply chain; CDP Supply Chain Program
JEL codes: M14, M41, Q50, Q54

Acknowledgments: I am deeply grateful to my committee members, Mingyi Hung, Shiheng Wang, Daniel Yang and Charles Hsu, for their guidance and support. I thank Zhihong Chen, Qingkai Dong, Yvonne Yanzi Han, Meretno Harjoto (discussant), Allen Huang, Hwa Young Kim, Qianqian Li, Charles McClure, Arthur Morris, Chao Tang, Emily Jing Wang, Bohyun Yang (discussant), Yue Zheng, and participants at the 2023 HKUST PhD seminar, 2025 HKUST accounting research seminar, 2025 EAA Congress, 2025 AAA SPARK Meeting, 2025 AFAANZ conference for helpful comments and suggestions. I thank discussions with Paddy Dixon, Emma Light, and Ben Robinson from the CDP. Any errors are my own.

Preliminary. Please do not circulate without the author's permission.

1. Introduction

In light of the challenges posed by climate change and increasing scrutiny from investors, stakeholders, and regulators, firms are increasingly concerned not only about their own environmental performance, but also about that of their supply chain partners. Given that a significant portion of greenhouse gas (GHG) emissions originates from upstream supply chains, there is a growing need to better understand and manage these emissions (CDP 2010, 2024; International Sustainability Standards Board (ISSB) 2022).[1] A crucial first step is for firms to gather information from suppliers about GHG emissions and climate change vulnerabilities, as reliable measurement of emissions is the foundation for meaningful action (Greenstone, Leuz, and Breuer 2023). In this study, I examine the effect of customer-initiated demand for carbon disclosures along the supply chain.

Firms managing supply chain emissions often encounter a lack of information from suppliers (World Economic Forum 2023). To tackle this, some firms, such as Walmart in 2008, have requested GHG data directly from suppliers. However, this approach can be costly. Additionally, firms increasingly need to measure and report Scope 3 emissions to provide a complete carbon footprint, which is challenging, as these emissions occur outside their operational boundaries (Bolton et al. 2021b; FTSE Russell 2024; Reichelstein 2024).[2] The GHG Protocol suggests using primary data from suppliers, or secondary data such as industry averages, even though the latter changes slowly and may not reflect short-term improvements. Ideally, the supplier-specific approach is more accurate, allowing firms to identify effective interventions rather than merely

[1] See also "Apple takes step toward curbing climate-warming emissions from its supply chain" (https://www.washingtonpost.com/climate-environment/2019/04/11/apple-takes-step-toward-curbing-climate-warming-emissions-its-supply-chain/).

[2] Scope 3 emissions include all other indirect GHG emissions that occur within a company's value chain, including both upstream emissions (originating from the production of goods or services acquired by the company) and downstream emissions (arising from the use and disposal of products or services sold).

changing procurement strategies (GHG Protocol Initiative 2013). In practice, however, firms face a scarcity of supplier data as carbon emission disclosures have not been mandated in most countries.

To address this information demand, a non-profit organization called the Carbon Disclosure Project (CDP) launched the Supply Chain Program (hereafter, "the CDP-SC program" or "the program") in 2007, to be implemented through annual information requests. This program has created a standardized process for reporting carbon emissions, risks, opportunities, and strategies within supply chains. After customer firms (hereafter, "CDP-SC customers") join and specify their suppliers, CDP surveys suppliers on behalf of customers. In addition to providing supplier firm-level carbon emissions, suppliers are encouraged to disclose granular emissions information tailored to specific customers or product lines. In this study, I use the CDP-SC program as a setting to examine the impact of customer-initiated demand for carbon disclosures.

While customers can reach out to their suppliers directly for emissions information, the CDP-SC program offers several distinct advantages over private communications. First, direct communications with a large and spread-out group of suppliers requires customers to invest substantial resources into acquiring relevant expertise. Otherwise, suppliers may receive multiple requests containing inconsistent questions and requirements, causing "survey fatigue" and reducing response rates. In contrast, the CDP has specialized expertise in designing comprehensive and reliable disclosure systems. It collaborates with policymakers such as the Sustainability Accounting Standards Board (SASB), and its questionnaire aligns with the latest and most relevant frameworks and standards.[3] This integration creates a one-stop shop for carbon disclosures.

Second, the CDP team is experienced in managing large-scale data requests, reducing costs for both customers and suppliers. For customers, it is costly to address survey inquiries across a

[3] Examples include the IFRS S2 (ISSB) climate standard, GHG Protocol, Global Reporting Initiative standards, and the Taskforce on Nature-related Financial Disclosures.

population of suppliers with diverse characteristics and concerns. In contrast, the CDP provides a scalable solution that alleviates resource demands to help suppliers complete surveys. For suppliers, disclosing once through the program can allow their data to be accessed by many customers. Notably, response rates are higher when relying on the program than when customers distribute surveys themselves (CDP 2008).

Third, participating customers are provided with comprehensive data analytics to support informed decision-making. For example, the supplier scorecard enables customers to identify emissions hotspots, and emissions inventory building reports assist in measuring upstream Scope 3 emissions.

Empirically, the program offers another two advantages for studying the impact of customer demand for GHG information. First, customer firms must sign up for the program, enabling the program to send requests to suppliers on their behalf. This setting enables the observation of time-series variations in customer demand for suppliers' GHG information, which can be viewed as exogenous shocks to suppliers. Second, since customer firms joined the program at different times, the staggered participation alleviates concerns about confounding events.

In accordance with disclosures serving a monitoring role (Lambert, Leuz, and Verrecchia 2007), I hypothesize that suppliers reduce direct emissions after their customer firms initiate requests for GHG information disclosures via the CDP-SC program. The granular and standardized GHG information provided by suppliers—at supplier-firm level (i.e., aggregate Scope 1 emissions), supplier-customer pair level, and specific product level—reduces information asymmetry that customer firms face regarding suppliers' emission performance (Christensen, Hail, and Leuz 2021). This allows customer firms to discover climate risks and emissions hotspots in the supply chain, and monitor and identify opportunities to engage suppliers in emissions reduction activities. The effectiveness of this monitoring and engagement stems from customer firms' bargaining power, which enables them to pressure suppliers (Pataoukas 2012; Dai et al. 2021). As a result, suppliers are incentivized to alter their behavior and undertake emission-reduction efforts.

However, there are arguments against my predictions. Customer firms may use the program for branding purposes without monitoring suppliers, which could lead suppliers to not taking the requests seriously. Additionally, the CDP does not verify suppliers' responses. These responses may lack reliability, weakening customers' motivation to assess and engage with suppliers. Furthermore, the program may not provide incremental information for customers who already have effective private communications with their suppliers.

My treatment sample consists of suppliers with at least one customer who joined the program during 2007-2019, collected via CDP Supply Chain annual reports. I identify all public suppliers from the FactSet Revere Supply Chain database and the CDP Supply Chain climate change public spreadsheets. For each treatment supplier, I take the earliest year that its customer firms joined the program as the first year of the treatment. I limit the event window to five fiscal years before and after the treatment year. The benchmark sample covers suppliers without any customer firm joining the CDP-SC program during 2007-2019. My main analysis focuses on the top 100 suppliers to CDP-SC customers. I create entropy balanced (EB) and propensity score matched (PSM) samples as two benchmark samples. The EB sample consists of 2,161 treatment suppliers and 7,157 benchmark suppliers, while the PSM sample consists of 1,431 treatment suppliers and 1,209 benchmark suppliers.

I employ a difference-in-difference approach to study the effects of customer demand for GHG information on suppliers' emissions performance. To measure supplier firms' direct emissions performance, I use Scope 1 emissions data from S&P Trucost. Consistent with my hypothesis, I find that compared to benchmark suppliers, treatment suppliers reduce Scope 1 emissions by 6.9% to 8%, after their customers have initiated requests for carbon disclosures via the program. This effect is economically significant, representing 1.83-1.85% of the standard deviation of treatment suppliers' Scope 1 emissions before the program. My findings remain robust to the use of alternative samples and measures.

I perform several cross-sectional tests to explore the underlying mechanisms. First, the documented effect is stronger among treatment suppliers whose customers have greater incentive to use requested data to monitor suppliers, as measured by customers' indirect emissions before joining the program, the use of suppliers' GHG information in decision-making, and their enrolling as premium members. Second, the effect on suppliers' Scope 1 emissions is stronger among treatment suppliers with stronger incentives to reduce carbon emissions, as measured by their decisions to publicize responses, emissions performance in the pre-period and home countries' environmental regulation and enforcement. Third, the effect is stronger among suppliers with poor bargaining power against their customers, as measured by how many of a supplier's customers are participating in the program, and the duration of the relationship with customers. Last, the effect is stronger when there is greater information asymmetry regarding GHG performance between suppliers and customers in the pre-period.

Additional analyses reveal that the program yields other outcomes for suppliers and customers. From the supplier side, treatment suppliers adopt more emissions reduction and environmental policies compared to benchmark suppliers. Treatment suppliers also attract more customers after exposure to the program. Moreover, customer firms increase their public disclosures about supply chain relationships, especially with suppliers who show a greater reduction in carbon emissions after being exposed to the program.

From the customer side, participating customer firms are more likely to disclose upstream Scope 3 emissions, report a more granular breakdown of these emissions, and utilize more data obtained from suppliers or value chain partners when measuring these emissions, compared to benchmark customer firms in the post-participation period. These findings indicate that the rich and granular data disclosed by suppliers enhances customers' information environment, enabling them to increasingly incorporate suppliers' data into their calculations and reporting of Scope 3 emissions.

My study contributes to the literature in several ways. First, it adds to studies examining customers' role in influencing suppliers' ESG performance. By documenting the spillover effects of socially responsible behavior (e.g., customers' ESG scores, carbon intensity) from customers to their suppliers (Dai, Liang, and Ng 2021; Asgharian et al. 2024; Schiller 2018; Cho et al. 2023), prior research has indicated an implicit governance role played by customers. My paper differs from prior literature by focusing on a directly observable channel through a centralized disclosure platform: customers' requests for granular GHG information, especially information related to the requesting customers' production processes. My setting helps address the challenge arising from the fact that customer requirements have remained generally unobserved in existing studies.

My study is most closely related to that of Bonetti et al. (2024), a concurrent working paper identifying spillover effects in climate disclosures from customers to their suppliers via the CDP. While their study focuses on suppliers' disclosure decisions, my research is more attentive to supplier firms' emissions performance, with a focus on the CDP-SC program.[4] In addition, while they examine the CDP's impact on suppliers, my study analyzes the outcomes for both suppliers and participating customer firms. Furthermore, while their study primarily concerns the

[4] They examine suppliers' emissions performance in an additional analysis as shown in their Table 10 Panel B.

impact of supplier and customer characteristics on suppliers' disclosure decisions, I connect the real effect to the key features of the CDP-SC program, such as premium membership and response status, illustrating the factors influencing the heterogeneous effectiveness of the centralized platform for supplier information requesting and reporting.

Second, my study adds to the literature on ESG disclosures. Prior studies have explored the effects of formal, regulation-based disclosure demands (Christensen, Floyd, Liu, and Maffett 2017; Chen, Hung and Wang 2018; Downar et al. 2021; Grewal Riedl and Serafeim 2019; Huang and Lu 2022; She 2021; Tomar 2023; Wang 2022), while I examine one channel of informal, market-driven disclosure requests. My study sheds light on the importance of the worldwide mandate of Scope 1 emissions by all firms (Bolton et al. 2021b; Mahieux, Sapra and Zhang 2025) , which would facilitate firms' management of their carbon footprints along supply chains, as well as the measurement of Scope 3 emissions.[5] My study adds to the literature on Scope 3 emissions (Bolton and Kacperczyk 2021; Carter, Lee and Yu 2025; Cho, Kim and Yang 2023; Deng, Hung and Wang 2024; Serafeim and Vélez Caicedo, 2022) by illuminating the factors influencing firms' Scope 3 disclosures.

Third, my study adds to the growing research on the CDP Supply Chain program (Jira and Toffel 2013; Hales 2023). It complements Cohen, Kadach, and Ormazabal (2023) who examine the effects of the CDP-investor program on surveyed firms' emissions disclosure decisions and environmental performance. While their study primarily tracks the effects of disclosure demand from institutional investors, mine focuses on customer firms who possess information needs and engagement methods that differ from those of institutional investors. Institutional investors

[5] IFRS S2 (Climate-related Disclosures) underscores the importance of obtaining supplier-reported data for value chain disclosure and transparency (see https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ifrs-s2-climate-related-disclosures/).

prioritize the financial implications of firms' emissions performance (Krueger, Sautner and Starks, 2020). On the other hand, customer firms seek granular GHG data for two main reasons: to manage emissions in their supply chains in order to minimize reputational risk, and to measure Scope 3 emissions. Furthermore, institutional investors typically keep an arm's length relationship with portfolio firms without engaging in direct business interactions, while customer firms have operational ties with suppliers through procurement and production activities. Thus, ex-ante, the insight from Cohen et al. (2023) may not apply to customer-supplier relationships.

Finally, my findings add to the literature on the effects and venues of information sharing between suppliers and customers. While prior literature has focused on sharing production parameters such as inventory levels and demand forecasts (Bushee, Kim-Gina, and Leung 2020; Cachon and Fisher 2000; Özer, Zheng and Chen 2011), my study extends to non-financial information. Additionally, while prior literature has generally assumed private communication between customers and suppliers, my study explores a centralized disclosure venue that reduces users' information disclosure and acquisition costs (Duguay, Rauter, Samuels 2023; Goldstein, Yang, Zuo 2023; McClure, Shi and Watts 2025).

2. Institutional Background and Hypothesis Development

2.1. Institutional Background

The CDP is a UK-based not-for-profit organization founded in 2000 to promote sustainable economic growth by encouraging firms to disclose their environmental impacts. It has developed a comprehensive and standardized reporting framework, distributes questionnaires, and compiles responses into a corporate climate change database. The CDP runs an investor program that surveys constituents of widely used indexes (Cohen et al. 2023).[6] In 2007, it launched the Supply Chain Program to create a standardized process for supply chain reporting on carbon emissions, risks, opportunities, and strategies. Through this program, customer firms can request disclosures from their suppliers, helping them better understand the carbon emissions embedded within supply chains (CDP 2008). Participating customer firms can choose to be a lead, premium, or standard member, each with varying fees and benefits.[7] Customer firms prefer the program over private communications due to its expertise in standardized disclosures, efficient disclosure request management, and insightful analysis.[8] Examples of data analysis include summary reports, data visualizations, and emissions inventory building reports. Lead and premium members receive additional services, such as customized data analysis, year-to-year benchmark reports, supplier maturity scales, and supplier performance scorecards.

Each year, customer firms submit a list of current suppliers to the program. The CDP notifies suppliers, inviting them to complete the questionnaire through the CDP portal, which usually opens in March and closes in October. Suppliers' participation is voluntary and free, with the CDP offering reporting support (i.e., education webinars). Customers may establish contractual requirements to encourage response and reward efforts with benefits such as contractual extensions and preferential financing rates (CDP 2024).

Suppliers receive standard climate change questionnaires and a specific supply chain module

---

[6] See also "How CDP Works" (https://cdn.cdp.net/cdp-production/comfy/cms/files/files/000/009/299/original/CDP_UK_Supply_Chain_Supplier_Disclosure_Support_Webinar_%28English%29_-_Session_1_notes.pdf).

[7] The annual membership fee for a standard member was about £16,000 in 2009 (CDP 2009). Lead members pay the highest membership fees. As of this writing, fees vary by business type, region, and discount policies.

[8] For example, AstraZeneca stated, "We rely on our suppliers' CDP submissions to gain consistent insight into our Scope 3 emissions. We want our suppliers to use a robust third-party platform so that when our suppliers submit data for AstraZeneca's Scope 3 programme, it can also be used with their other customers. We recognize the need for common approaches to reporting, to simplify processes and accelerate sustainability." (see https://www.cdp.net/en/insights/astrazeneca-using-purchasing-power-to-accelerate-action).

called "SC Supply Chain." The standard climate change questionnaires include questions regarding firm-level GHG data and other climate-related topics. The supply chain module includes four sections that request granular GHG data. Appendix A provides excerpts from the supply chain module.

The module begins with the "Supply chain introduction," where suppliers provide descriptions of their firms. Next, the "Allocating your emissions to your customers" section features a table where suppliers are asked to report emissions related to each requesting customer. It guides suppliers in allocating emissions to each requesting customer based on the goods or services sold to that particular customer. Its drop-down menu allows suppliers to view a list of requesting customers, select a specific customer and provide relevant data. Building on this, the "Collaborative opportunities" section allows suppliers to propose mutually beneficial climate-related projects, and the "Action exchange" section evaluates suppliers' willingness to participate in emission reduction activities. Lastly, the "Product (goods and services) level data" section asks for emissions associated with individual products or services, detailing the product type and stock-keeping unit (SKU). Suppliers are also asked to report emissions across all stages of goods and services' life cycles, providing a comprehensive view of the carbon footprint. Though the CDP does not verify responses, questions about verification status, calculation methodologies, the identification of GHG sources, and explanations for changes help customers assess responses' credibility.

Responses to the entire supply chain module remain private and accessible only to those customers who request them.[9] Customer-specific questions are only accessible to relevant customers, thereby protecting proprietary data.

---

[9] Suppliers can mark their responses to the standard climate change questionnaire as "public" or "private." Public responses are accessible to the public free of charge.

2.2. Hypothesis Development

A primary benefit of corporate disclosures is that they mitigate information asymmetries and facilitate monitoring activities by corporate outsiders (Christensen, Hail, and Leuz 2021; Healy and Palepu 2001; Lambert, Leuz, and Verrecchia 2007). The disclosures requested via the CDP-SC program give customers insight into supplier practices and identify opportunities for engagement, ultimately prompting suppliers to reduce emissions.

The extensive and granular disclosures mitigate the information asymmetry customers face (Cho, Lee and Pfeiffer 2013). These disclosures include GHG data at the supplier-firm level, supplier-customer pair level, and product level, which are often limited in public filings and costly to obtain through private communications. With this data, customers can identify suppliers with high climate risks that could harm their reputations or supply chain stability. Additionally, customers can leverage the data to estimate their upstream Scope 3 emissions, which include a substantial portion of suppliers' direct emissions (Matthews, Hendrickson, and Weber 2008). By reporting their contributions to customers' Scope 3 emissions and detailing emissions at the product or service level, suppliers provide up-to-date primary data that is more representative of supply chain activities (ISSB 2023). Furthermore, suppliers' disclosures, along with the CDP's data analysis, are in consistent and standardized formats. This facilitates comparisons across firms (Cohen et al. 2023). In sum, detailed carbon disclosures allow customers to monitor their suppliers, identify emissions hotspots, and thus, drive emissions reductions.

Anecdotal evidence supports my argument. For instance, Nissan Motor monitors suppliers' response rates and helps them lower energy costs and emissions. Similarly, Philips utilizes the program to gather a wealth of information on suppliers' climate activities, and has developed strategies such as offering "light-as-a-service", to achieve carbon savings without up-front investment (CDP 2014, 2016, 2017).

The monitoring and engagement might be effective because customers possess the power to influence supplier behavior. Prior work suggests that customers have a significant effect on suppliers' operating performance (Pataoukas 2012), disclosures (Ellis, Fee, and Thomas 2012; Crawford, Huang, Li and Yang 2020; Chen, Hu, Yao and Zhao 2022), environmental and social performance (Schiller 2018), and socially responsible behavior (Dai et al. 2021). Through the program, customer requests highlight customers' dedication to supply chain sustainability, increasing suppliers' awareness of the importance of carbon emissions. In situations where suppliers have low bargaining power against customers, their pressure intensifies, as they are concerned about losing contracts or customers after revealing unsatisfactory GHG performance. As a result, suppliers are likely motivated to improve emissions performance.

The above discussion leads to my hypothesis:

Hypothesis: *Suppliers reduce Scope 1 emissions following their customers' requests for carbon disclosures.*

There are several reasons that my hypothesis may not hold. First, customers may join the program mainly for marketing purposes rather than to utilize the actual disclosures to monitor suppliers. Second, suppliers might necessarily not take requests seriously, as asking for information does not necessarily indicate a requirement for emission reductions. Third, suppliers' responses may lack reliability. Since the CDP does not verify suppliers' responses, they might underreport emissions, weakening customers' incentives to engage. Consequently, suppliers might not feel compelled to take action. Finally, for customers with existing private communication channels and collaborations with suppliers, the program might not provide any additional information or pressure to drive further action, thus limiting its effectiveness.

3. Sample and Research Design

3.1. Sample and Data

To construct my supplier sample, I start with the universe of customers that joined the CDP-SC program, obtaining their names and participation years from the CDP Supply Chain annual reports from 2007 to 2019. Table 1 Panel A outlines the sample selection procedures. I exclude customers with a membership duration of less than three years due to their low commitment to the program.[10] For long-term CDP-SC customer firms, I obtain their publicly listed suppliers from 2003 to 2023 from the FactSet Revere Supply Chain database. I do not include private suppliers in the sample due to the lack of associated accounting variables. I also obtain public suppliers from the CDP Supply Chain climate change public spreadsheets (hereafter, "the CDP-SC spreadsheets"), which include any suppliers that have submitted public responses to CPD-SC customers but have been omitted from FactSet.[11]

Next, I create the treatment sample, starting with suppliers with at least one customer joining the program, consisting of those identified from FactSet and CDP-SC sheets. I exclude suppliers whose relationships with CDP-SC customers ended before the year those customers joined the program, as they were unaffected due to their inactive relationships. Ideally, my treatment sample should consist of suppliers requested by CDP-SC customers each year. However, the program does not provide a list of requested suppliers along with their requesting customers. The CDP-SC spreadsheets include only those suppliers for whom public responses were both requested and submitted, omitting those who had submitted private responses or had chosen not to respond.

[10] These customers lack long-term incentives because they may benchmark suppliers only once or twice, find the disclosures less informative than expected, or perceive the membership fee as too expensive.
[11] FactSet gathers customer-supplier relationships primarily from public disclosures, and it may omit some suppliers who are not publicly disclosed.

To address this empirical challenge, I collect statistics from the CDP-SC annual reports, as presented in Appendix B. This table displays the annual number of CDP-SC customers, the number of suppliers for whom survey completion had been requested, the number of suppliers who had responded, and the number of suppliers for whom responses had been publicized. These figures indicate that, on average, customers survey approximately 100 suppliers each year. Customers typically prioritize their most important suppliers due to their greater economic importance, higher emissions, and heightened public scrutiny. Additionally, CDP-SC annual reports and customer firms' voluntary disclosures show that customers tend to focus on surveying their major suppliers (CDP 2008).[12] Therefore, in my main analysis, I keep the top 100 suppliers for each customer based on supplier firm size.[13]

For each treatment supplier, I identify the event year as the earliest year that its customers joined the program. For suppliers covered by the CDP-SC spreadsheets but not FactSet, I do not know the identity of their CDP-SC customers, so I use the earliest year in which a supplier submitted a response as the event year. I exclude all event years after 2020. The event window includes five fiscal years before (i.e., the [-5, -1] years) and after (i.e., the [0, 4] years) the event year. If all customers of a treatment supplier joined the program prior to their relationship with the supplier, I use the earliest year the supplier had formed a relationship with those customers as the event year.

The benchmark sample consists of suppliers without any customers participating in the program from 2007 to 2019. I merge the treatment and benchmark samples with Global Vantage

[12] For example, Dell surveyed major suppliers in 2007 (CDP 2008); Samsung Electronics planned to survey its most important 100 suppliers after joining the CDP-SC program (see https://www.samsung.com/us/aboutsamsung/sustainability/environment/climate-action/).
[13] For each year, I obtain a customer's top 100 suppliers. If a customer has fewer than 100 suppliers, I include all of them in the analysis. In untabulated analysis, my results hold when ranking the top 100 suppliers by revenue.

for firm characteristics and S&P Trucost for emissions data. Trucost is a widely used provider of corporate carbon data (Bolton and Kacperczyk 2021; Cohen et al. 2023; Gipper, Sequeira, and Shi 2024). It collects carbon emissions data from firms' public disclosures, such as annual reports, CDP surveys, and corporate websites, and estimates emissions when firms do not publicly disclose this information. Trucost also engages with firms, and if it finds firms' supplementary data useful, it incorporates the data after a quality check. I exclude suppliers with missing Trucost emissions data, control variables or industry information, and those in the financial (NAICS2=52) or public administration (NAICS2=92, 99) industries. To mitigate potential measurement errors in Scope 1 emissions, I exclude firm-years with an absolute growth rate in Scope 1 emissions exceeding 500%, as well as those with combined Scope 1 and 2 emissions below 1,000 mt CO2e (Berg, Ma, and Streitz 2024). I exclude countries with five or fewer suppliers. To ensure that changes in carbon emissions are not due to changes in sample composition over time, I require a supplier to have at least one observation in each of the pre- and post-periods.

To enhance comparability between treatment and benchmark suppliers, I create two benchmark samples. First, I apply entropy balancing year by year based on the first and second moments of control variables, with a tolerance level of 0.01 (Hainmueller 2012; McMullin and Schonberger 2022). Second, I construct a sample of propensity-score matched firms. Suppliers are eligible for matching if they are from countries with more than five suppliers and have at least one observation with all control variables and emissions data in both pre- and post-periods. I estimate a logit regression using average control variables and Scope 1 emissions from the three years before the event, including industry fixed effects, due to correlations of carbon emissions within industries. Matching is performed for each event year without replacement using a caliper of

0.05.[14] Appendix C reports the PSM estimation results.

I refer to the sample including both the treatment and the entropy-balanced benchmark suppliers as the "EB sample", and the sample including both the treatment and the propensity-score matched suppliers as the "PSM sample". As reported in Table 1 Panel A, the "EB sample" consists of 2,161 treatment suppliers and 7,157 EB benchmark suppliers, and the "PSM sample" includes 1,431 treatment suppliers and 1,209 benchmark suppliers. Table 1 Panel B presents the sample distribution by year. Both the EB and the PSM samples are balanced across years by construction. Table 1 Panel C displays the sample distribution by economy, with the U.S. having the most suppliers[15]. Finally, Table 1 Panel D reports industry distribution, showing comparable industry distribution between treatment and benchmark suppliers, with manufacturing (NAICS2=31, 32, 33) being the top industry segment.

3.2. Research Design

I examine the impact of customer demand for GHG information (reflected by their adoption of the CDP-SC program) on suppliers' carbon emissions performance using the following model:

$$Y_{i,t} = \beta_0 + \beta_1 Treat_i \times Post_{i,t} + \sum \gamma_i Control\ Variables + Firm\ FE + Year\ FE + \varepsilon_{it} \tag{1}$$

In this model, *i* and *t* denote the supplier firm and year, respectively. My dependent variable is *Ln(Scope 1)*, the natural logarithm of a supplier firm's Scope 1 emissions volume. *Treat* is a

[14] To maximize the sample size, I allow for replacement in matching across event years. For example, a benchmark supplier matched in the event year 2008 can also be used for matching in the event year 2018. Therefore, the number of firms in the PSM treatment sample differs from that in the PSM benchmark sample.
[15] The PSM samples include countries not in the EB sample, because the EB sample requires complete controls and emissions data for all firm-years before excluding countries with five or fewer suppliers. The PSM sample begins with a broader matching pool, including suppliers from countries with more than five suppliers, as long as there is at least one firm-year with complete data in both the pre- and post-periods.

binary variable equal to 1 if a supplier has at least one customer which has adopted the CDP-SC program, and 0 otherwise. *Post* is a binary variable equal to 1 starting from the earliest year a supplier's customer joined the program onward, and 0 otherwise. For suppliers omitted by FactSet, *Post* is a binary variable that equals 1 starting from the earliest year of its response publication and 0 otherwise. My variable of interest is the coefficient of the interaction term $Treat$ × *Post*, β_1, which captures the change in treatment suppliers' Scope 1 emissions after the event, relative to the change in benchmark suppliers' Scope 1 emissions. To control for time-invariant firm characteristics, I include supplier firm fixed effects. To account for time-invariant heterogeneity within supplier firms, I include year fixed effects.

I include several variables from prior studies to explain Scope 1 emissions: *Size*, the log of total assets; *Leverage*, total liabilities divided by total assets; *ROA*, return on assets; *Sales Growth*, percentage change in annual sales; *Tangibility*, tangible assets (property, plants, and equipment) divided by total assets; *R&D*, R&D expenditures; and *TobinQ*, growth opportunities. Appendix D provides variable definitions. To mitigate the influence of any extreme values, all continuous variables are winsorized at 1% and 99% in the sample. In addition, all *t*-statistics are computed with robust standard errors clustered by supplier firm.[16]

3.3. Descriptive Statistics

Table 2 presents descriptive statistics of the variables in my main analyses for the pre- and post-periods. Panel A presents descriptive statistics for the EB treatment and benchmark samples without applying entropy-balancing weights, illustrating the differences in variable distribution prior to conducting the entropy balancing. Panels A and B indicate that on average, EB and PSM treatment suppliers exhibit lower Scope 1 emissions in the post-period compared to the pre-period.

[16] In untabulated analysis, my results hold when using country cluster.

Though benchmark suppliers of the PSM sample also experience a decrease in Scope 1 emissions in Panel C, the magnitude is less than that of treatment suppliers in the PSM sample. Panels B and C show that the decrease in *Ln(Scope 1)* is greater for the PSM treatment suppliers than for the benchmark suppliers. While the magnitude of difference appears comparable, it is based on a univariate test and does not account for my full empirical specification.

4. Empirical Results

4.1. Baseline Results

Table 3 Panel A presents the regression results. Columns (1)–(3) and (4)–(6) display changes in Scope 1 emissions following the event for the EB and the PSM samples, respectively. I report the baseline model in Columns (1) and (4), and the full regression specification with firm and year fixed effects in Columns (2) and (5). Consistent with my hypothesis, the coefficient for the interaction term *Treat* × *Post* is negative and significant in these specifications for both the EB and the PSM samples. This suggests that treatment suppliers experience a greater decrease in Scope 1 emissions than benchmark suppliers after the event. In terms of economic significance, Columns (2) and (5) indicate that relative to changes in Scope 1 emissions in the benchmark suppliers in the EB and the PSM samples, treatment suppliers experience a decrease in Scope 1 emissions, by 8.0% and 6.9%, respectively. These changes are equivalent to 1.85% and 1.83% of the standard deviation of treatment suppliers' Scope 1 emissions before the event.[17]

To assess the validity of the parallel trends assumption for the difference-in-difference

[17] 1.85%=8.0%×3.19/13.82 and 1.83%=6.9%×2.49/9.41, where 3.19 and 13.82 are the mean and standard deviation (in million metric tonnes) of treatment suppliers' Scope 1 emissions during the pre-period for the EB sample. Similarly, 2.49 and 9.41 are the mean and standard deviation (in million metric tonnes) of treatment suppliers' Scope 1 emissions during the pre-period for the PSM sample.

specification, I follow Bertrand and Mullainathan (2003) to run a timing regression. I set *Year -1* as the benchmark year and replace *Post* with nine year indicators (i.e., Years -5 to -2 and Years 1 to 4). As is shown in Columns (3) and (6), the coefficients for *Year -5* × *Treat, Year -3* × *Treat,* and *Year -2* × *Treat* are not significantly different from zero. This suggests similar trends in Scope 1 emissions for treatment and benchmark suppliers in the pre-period. From *Year 0* in Column (3) and *Year 1* in Column (6), the interaction terms' coefficients are negative and significant, indicating greater decreases in Scope 1 emissions among treatment suppliers in the post-period. Overall, there appears to be no anticipation effect, and customers' adoption of the CDP-SC program has an effect after it occurs.

In summary, these results imply that suppliers reduce Scope 1 emissions following their customers' participation in the program, reflecting the real effects of customer demand for suppliers' carbon disclosures.

4.2 Robustness Checks

Panel B of Table 3 presents robustness checks. In addition to the CDP-SC program, the CDP also runs an investor program that surveys constituents of widely used indexes which are of interest to institutional investors, such as the S&P 500 and MSCI ACWI (Cohen et al. 2023). To mitigate concerns that sample suppliers may also be influenced by investors' survey requests, I exclude any suppliers that are also surveyed in the investor program and have submitted public responses.[18] My results remain robust (Table 3 Panel B Columns (1) and (2)). Second, I remove any suppliers which are omitted by FactSet and only present in the CDP-SC spreadsheets, and the inferences are similar (Table 3 Panel B Columns (3) and (4)). Third, my selection of the top 100 suppliers may miss some suppliers that have actually been surveyed. Thus, I expand my sample by including all

[18] These suppliers are obtained from the variable "program type" in the CDP Public Climate Change data.

suppliers, regardless of their importance to CDP-SC customers. The results in Columns (5) and (6) indicate that CDP-SC customers have a significant effect on all their suppliers, not only the top suppliers. Last, I use Scope 1 emission intensity from Trucost as an alternative emissions measure in Columns (7) and (8), and the results are comparable to those reported in Table 3 Panel A.

In untabulated analysis, I conduct a placebo test using pseudo-event years to mitigate the concern that my results are driven by confounding events correlated with the timing of CDP-SC customers' enrollment in the program. Treatment suppliers are randomly assigned pseudo-event years that are shifted from the original event years by a range of 0 to 3 years. Then, I re-estimate logit regressions to construct a propensity score-matched sample, and my findings do not hold when using placebo event years. Additionally, to address concerns with staggered difference-in-difference models (Baker, Larker and Wang 2022; Barrios 2024), I perform stacked regressions and my results hold. Furthermore, I control for mandatory ESG disclosure regulations (Krueger, Sautner, Tang and Zhong 2024) and the results remain robust. Finally, I use suppliers' public responses to the CDP as the dependent variable, and find that treatment suppliers are more likely to provide such disclosures.

5. Cross-sectional Analyses

This section explores the mechanisms underlying the real effects of the customers' requests for carbon disclosures. I explore customers' incentives to monitor suppliers, suppliers' incentives, and the dynamics of bargaining power and information asymmetry.

5.1. Cross-sectional Analysis of Customers' Incentives

Customers' incentives to use collected information to discipline suppliers influence their monitoring and engagement effectiveness. I expect stronger effects when customers have greater incentives to use suppliers' disclosures in disciplinary activities, and explore three measures to capture such incentives.

First, CDP-SC customers utilize information on suppliers' emissions, which contributes to their upstream Scope 3 emissions. Customers with higher pre-participation indirect emissions are more likely to use this platform to gather relevant information and discipline suppliers. To perform this test, I evaluate customers' average upstream Scope 3 emissions from Trucost over the three years before participation, classifying them into high and low groups based on the median values. I exclude any suppliers omitted by FactSet due to the inability to identify their customer-supplier relationships. Then, I count the high-emissions customers for each treatment supplier, and categorize them into *High Incentive* and *Low Incentive* groups based on country-industry median values.

Second, I explore whether customers utilize suppliers' GHG information. Customers can integrate the data into supply chain management and the decision-making process.[19] To assess whether customers utilize suppliers' GHG information, I analyze responses to question 14.4c from the CDP Climate Change questionnaire: "If you have data on your suppliers' GHG emissions and climate change strategies, please explain how you make use of that data."[20] I classify CDP-SC customers as information users if they respond positively, excluding those stating, "We do not have any data." For each supplier, I count the customers using GHG information, and partition suppliers into high and low subgroups based on country-industry median values.

Third, I investigate customers' commitment to the program. The membership type chosen

[19] For example, Eni analyzed suppliers' GHG emissions and climate change strategies, focusing on the most relevant information, such as supplier categories with the highest impact on emissions and existing reduction actions and measures, in order to explore improvement actions (CDP 2015).
[20] This question was included in the questionnaire from 2013 to 2016, resulting in smaller sample sizes.

reflects their commitment to sustainable supply chains and interest in understanding response data. Lead and premium members receive more data analytics, indicating greater interest in learning and using suppliers' GHG information. Since most participating customers are standard members, I collect membership type from the CDP-SC annual reports, and group lead and premium members as premium customers. Then, I count the premium customers for each treatment supplier, partitioning them into high and low subgroups based on country-industry median values.

The results are presented in Table 4 Panel A. The coefficient for *Treat* × *Post* × *High Incentive* is negative and significant in both the EB and the PSM samples. The difference in coefficients between the two groups is negative, and significant in Columns (1), (3), and (5), suggesting that suppliers in the high incentive group experience a greater reduction in Scope 1 emissions.

Overall, these results suggest that the disciplinary effect is more salient when customers have high incentives to use suppliers' GHG information.

5.2. Cross-sectional Analysis of Suppliers' Incentives

In this section, I examine suppliers' incentives. First, I investigate whether suppliers that publicly respond to CDP-SC customers achieve greater emission reductions. Public responses to the standard climate change questionnaire are posted on the CDP website, attracting scrutiny from investors and stakeholders, which may incentivize suppliers to improve emissions performance. I categorize treatment suppliers into a *High Incentive* group if they submitted public responses, and a *Low Incentive* group if they did not. Columns (1)–(2) of Table 4 Panel B show that the coefficients for *Treat* × *Post* × *High Incentive* are negative and significant in both samples. The negative difference in coefficients between the two groups is significant in the EB sample.

Next, I analyze suppliers' emissions in the pre-period. Given that suppliers face increased pressure to provide emissions information after receiving survey requests, they may be concerned that customers will use emissions data in benchmarking processes, cost reduction methods, and even contract termination (CDP 2009). Thus, I expect suppliers with higher pre-period emissions to have stronger incentive to reduce them. I collect Scope 1, Scope 2, and upstream Scope 3 emissions during the most recent three years in the pre-period and compute the average ratio of Scope 1 emissions to total emissions. Then, I classify treatment suppliers into *High* and *Low Incentive* subgroups based on country-industry median values. Columns (3)–(4) of Table 4 Panel B show that suppliers in the *High Incentive* group exhibit greater emission reductions.

Finally, I examine the role of environmental regulation and enforcement in supplier countries. I expect that suppliers in countries with strong environmental regulations and enforcement will reduce emissions more effectively, as customers may be concerned about suppliers' potential violations. To address this, I obtain the stringency of environmental regulation score (SER) and the enforcement of environmental regulation score (EER score) from the World Economic Forum's Travel & Tourism Competitive reports from 2011–2017, and combine them into a single variable SEER (Ben-David et al. 2021), defined as (SER×EER)/7. I compute the mean SEER for each supplier country and partition them into *High* and *Low Incentive* groups based on the sample median. Columns (5)–(6) in Table 4 Panel B show that suppliers in the *High Incentive* group exhibit greater emissions reductions.

Taken together, these results indicate that suppliers with greater incentives to improve emissions performance reduce emissions more after their customers have participated in the program.

5.3. Cross-sectional Analysis of Bargaining Power between Suppliers and Customers

I also explore how suppliers' bargaining power against CDP-SC customers affects their behavior. I posit that suppliers with weaker bargaining power are more likely to improve emissions performance. I assume that a supplier has weaker bargaining power when it has: (1) more CDP-SC customers (Asgharian et al. 2024); and (2) longer relationship durations with CDP-SC customers (Darendeli et al. 2022).[21]

Firstly, suppliers with many CDP-SC customers may face multiple simultaneous requests. This concentrated attention and the inflow of requests can pressure them to meet customer expectations. To quantify this, I count the CDP-SC customers for each supplier and classify suppliers with counts above country-industry values as having weaker bargaining power.

Secondly, suppliers with longer relationships with CDP-SC customers are likely more economically dependent on them and more inclined to meet their needs. I calculate the duration of each supplier's association with CDP-SC customers up to *Year 2*. Then, I calculate the average duration for each supplier, and partition suppliers within each country-industry into a *Low Bargain* subsample if their average duration exceeds the country-industry median value, and into a *High Bargain* subsample if it is below.

The findings in Columns (1)–(2) of Table 4 Panel C suggest that suppliers with more CDP-SC customers reduce Scope 1 emissions more, as indicated by the negative and significant coefficient of *Treat* × *Post* × *Low Bargain*. The difference in coefficients between the two groups is negative and significant in the EB sample. Similarly, Columns (3)–(4) suggest that suppliers with longer relationships achieve greater emissions reductions.

In sum, suppliers with weaker bargaining power against CDP-SC customers experience a greater reduction in emissions compared to those with stronger bargaining power, highlighting the impact of customer dependence on suppliers' emissions performance.

[21] I exclude any suppliers omitted by FactSet due to the inability to identify their customer-supplier relationships.

5.4. Cross-sectional Analysis of Information Asymmetry between Suppliers and Customers

If the program effectively reduces information asymmetry between customers and suppliers, customers can learn from suppliers' carbon disclosures and make more informed decisions, especially for those suppliers from whom information is costly to obtain. I predict that suppliers having high information asymmetry with customers in the pre-period may reduce Scope 1 emissions more than those with low information asymmetry. I assume that there is high information asymmetry when a supplier is opaque about its emissions in the pre-period.

I obtain suppliers' Scope 1 disclosure data from Trucost to construct a proxy for information asymmetry.[22] Then, I classify suppliers that voluntarily disclosed Scope 1 emissions in both *Year -2* and *Year -1* as *Low Information Asymmetry*, and categorize the others as *High Information Asymmetry*. Table 4 Panel D shows that the effect is stronger among suppliers with high information asymmetry, suggesting that the program effectively reduces information asymmetry regarding suppliers' GHG performance.

6. Additional Supplier Analyses

6.1. Suppliers' Practices

I argue that the observed decrease in suppliers' emissions is driven by increased customer efforts to monitor and discipline them. The evidence in Section 5 is consistent with this. In this section, I examine suppliers' practices to provide corroborating evidence.

If CDP-SC customers intensify their engagement with suppliers, these suppliers may be motivated to undertake relevant emission reduction activities. For example, Snam, an energy

[22] Trucost item "di_319403_text" states the sources of Scope 1 disclosure (i.e., "Exact Value from Annual Report/10K/Financial Accounts Disclosure", "Value derived from data provided in Environmental/CSR"). I categorize a firm-year as self-reported if Trucost collects its Scope 1 data from the firm's disclosures.

infrastructure company in the treatment sample, replaced its grey cast-iron network with higher-performance piping (Snam 2015). To test my conjecture, I analyze changes in emission reduction policies and the number of environmental policies using Refinitiv data.[23] Table 5 shows that treatment suppliers are more likely to adopt emission reduction policies and implement more environmental policies, with significant increases in the EB samples. Untabulated analysis shows that treatment suppliers receive higher environmental scores. These findings support the notion that suppliers undertake real efforts to improve emissions performance.

6.2. Analysis of Economic Consequence

Next, I explore whether treatment suppliers enjoy other benefits following their customers' adoption of the CDP-SC program. For those treatment suppliers that lowered their Scope 1 emissions, improved emissions performance may attract more customers (Darendeli et al. 2022). To compare the changes in customer growth between treatment and benchmark suppliers, I use FactSet to measure the number of unique customers for each supplier-year and the number of unique new customers that each supplier-year has attracted.

Table 6 presents the results. In Columns (1) and (2) the total number of customers is the dependent variable, while in Columns (3) and (4) the number of new customers is the dependent variable. All columns report significant positive coefficients on *Treat* × *Post*, implying that treatment suppliers experience a greater increase in both the number of customers and new customers, compared to benchmark suppliers in the post-period. These results suggest that suppliers expand their customer bases, highlighting the potential for improving market position through environmentally responsible practices.

6.3. Analysis of Customers' Supply Chain Disclosures

[23] I obtain a supplier's emission policies for 1,151 (out of 2,161) EB treatment suppliers, 2,458 (out of 7,157) EB benchmark suppliers, 705 (out of 1,431) PSM treatment suppliers, and 603 (out of 1,209) PSM benchmark suppliers.

I predict that customer firms are more likely to disclose relationships with treatment suppliers that have improved emissions performance in order to improve their reputations and strengthen stakeholder relationships (Shi et al. 2024). I use FactSet to track which party of a business pair (the customer or the supplier) publicly discloses their relationship. For each supplier, I count how many customers disclose their connection and rerun the regression with this measure as the dependent variable. Columns (1) and (2) in Table 7 show that treatment suppliers experience a greater increase in customers disclosing their customer-supplier relationships in the post-period, compared to benchmark suppliers.

To explore the heterogeneous impact, I categorize treatment suppliers into high and low groups based on their percentage change in emissions within the industry in the post-period. For each treatment supplier, I compute the average percentage change in Scope 1 emissions during the three years after the event. Then, I create a binary variable, *More Emission Reductions*, which equals 1 if a supplier's average percentage change is below the median value, and 0 otherwise. For the remaining treatment suppliers, I create a binary variable, *Less Emission Reductions*. Columns (3)–(4) of Table 7 reveal positive and significant coefficients for *Treat* × *Post* in both groups, with the *More Emission Reductions* group showing a significantly higher coefficient in the EB sample. This indicates that treatment suppliers with superior emissions performance in the post-period attract more customer disclosures, suggesting that improved emissions performance leads to more visible supply chain relationships.

7. Additional Analyses of CDP-SC Customers

In this section, I examine the benefits that customer firms gain from participating in the program, focusing on changes in Scope 3 disclosures. One incentive for customers to demand carbon disclosures via the program is the improved ability to measure and benchmark upstream Scope 3 emissions. For instance, Kellogg's (the food company) joined the program after committing to science-based targets in 2015. One of its initial obstacles to delivering the Scope 3 emissions target was to establish an accurate baseline for its 2015 Scope 3 emissions. This was addressed by asking suppliers to report high-quality primary data through the program (CDP 2018).

Measuring upstream Scope 3 emissions requires collecting and aggregating suppliers' relevant direct emissions (ISSB 2023). Without suppliers' disclosures, customer firms often rely on less reliable and less timely industry estimates (Reichelstein 2024). This dependence on secondary data creates challenges for both customer firms and external information users. The program tackles this issue by facilitating carbon disclosure requests, thereby improving customers' information environment (Cho et al. 2013). The wealth of data at various levels in standardized formats—such as supplier firms, supplier-customer pairs, and product lines—is useful to customer firms. Such granular and structured data allows them to aggregate primary data from suppliers, improving the reliability and accuracy of upstream Scope 3 emissions calculations, while reducing costly information acquisition. Thus, I predict that CDP-SC customers are more likely to provide upstream Scope 3 disclosures and its breakdown categories. Furthermore, I expect these customers to utilize more detailed data provided by suppliers in their calculations.

I construct a PSM sample by matching each long-term CDP-SC customer to a benchmark customer. I estimate a logit regression using control variables from one year prior to the event. Each CDP-SC customer's enrolment year serves as the pseudo treatment year for the matched benchmark customer. I obtain customers' disclosures of Scope 3 emissions from their responses to the CDP Climate Change questionnaire (see excerpts in Appendix E). Then, I create a constant sample by requiring that a sample customer has submitted responses to the CDP in both the pre-and post-periods, with the event window limited to four years before and after the treatment year. In the questionnaire, firms are asked to report emissions for each Scope 3 category and the percentage of emissions calculated using data obtained from suppliers or value chain partners. This quantifies the extent of supplier information that customers use when calculating emissions for the individual Scope 3 category. For each firm-year, I define this measure's average across all upstream Scope 3 categories as *Ave Usage Upstream Scope 3*.

Table 8 presents the results. Column (1) shows a positive and significant coefficient for *Treat* × *Post*. This suggests that CDP-SC customers are more likely to disclose upstream Scope 3 emissions to the CDP compared to benchmark customer firms after joining the program. Column (2) reveals that these customers are more likely to provide Category 1 Scope 3 emissions (purchased goods and services), for which the granular data from suppliers is particularly useful. Column (3) indicates that CDP-SC customers disclose a greater number of upstream Scope 3 categories.

The results regarding the use of supplier data are presented in Columns (4) and (5). The dependent variable is the average percentage of data used across upstream Scope 3 categories in Column (4) and the percentage of data used in Scope 3 Category 1 in Column (5). Both columns display positive and significant coefficients for *Treat* × *Post*, indicating that CDP-SC customers utilize more data from suppliers or value chain partners than benchmark firms in the post period.

Overall, the above results suggest that CDP-SC customers increase upstream Scope 3 disclosure and rely on more supplier data after their participation. This supports the notion that customers benefit from the enhanced information environment.

8. Conclusion

In this study, I have examined the effect of customer demand for carbon disclosures along the supply chain. My analysis exploits customers' staggered participation in the CDP Supply Chain Program, which enables them to request GHG information from suppliers at both the firm level and a granular level tailored to customers' specific needs.

My main analysis has focused on the top 100 suppliers of CDP-SC customers. I find that treatment suppliers experience a decrease in Scope 1 emissions following their customers' enrollment in the program, compared to benchmark suppliers. When exploring the underlying mechanisms, I leverage the program's unique features. I find that the decrease in Scope 1 emissions is more pronounced when customers have stronger incentives to monitor emissions along supply chains and have greater bargaining power against their suppliers, when suppliers face greater pressure to reduce emissions, and when there is greater information asymmetry between suppliers and customers.

Additional analyses reveal that suppliers adopt more emission reduction and environmental policies than benchmark suppliers. The program benefits both suppliers and customers. Suppliers experience an expanded supply chain network. Moreover, customers are more likely to publicly reveal their supply chain relationships with suppliers that achieve greater emissions reductions. Additionally, customers participating in the program show an increase in upstream Scope 3 disclosures and a higher number of reported upstream Scope 3 categories. When measuring Scope 3 emissions, these customers rely on more data from suppliers, reflecting an enhanced information environment resulting from the requested carbon disclosures.

I acknowledge the limitation arising from lacking access to detailed GHG data (e.g., GHG per SKU) in suppliers' responses to the supply chain module, which limits further analysis that might interest readers.

Overall, my study suggests that customer demand for carbon disclosures is associated with improved emissions performance among suppliers, and also benefits customers' Scope 3 emissions reporting. This highlights customers' role in driving sustainable practices along the supply chain.

References

Asgharian, H., M. Dzielinński, and Z. Hashemzadeh. 2024. Green links: Corporate networks and environmental performance. *Review of Finance* 28, 1027–1058.

Baker, A. C., D. Larcker, and C. Wang. 2022. How much should we trust staggered difference-indifferences estimates? *Journal of Financial Economics* 144, 370–395.

Barrios, J. M. 2024. Staggeringly Problematic: A primer on staggered DiD for accounting researchers. Working paper, Yale University.

Ben-David, I., Y. Jang, S. Kleimeier, and M. Viehs. 2021. Exporting pollution: where do multinational firms emit CO_2? *Economic Policy* 36, 377–437.

Berg, T., L. Ma, and D. Streitz. 2023. Out of sight, out of mind: Divestments and the global reallocation of pollutive assets. Working paper, Goethe University and IWH Halle.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* 111, 1043–1075.

Bolton, P, and M. T. Kacperczyk. 2021a. Do investors care about risk? *Journal of Financial Economics* 142, 517–549.

Bolton, P, and M. T. Kacperczyk. 2023. Global pricing of carbon transition risk. *The Journal of Finance* 78, 3677–3754.

Bolton, P, S. J. Reichelstein, M. T. Kacperczyk, C. Leuz, G. Ormazabal, and D. Schoenmaker. 2021b. Mandatory corporate carbon disclosures and the path to net zero. *Management and Business Review* 3, 21–28.

Bonetti, P., Y. En, I. Kadach, and G. Ormazabal. 2024. Climate disclosures and decarbonization along the supply chain. Working paper, IESE Business School.

Bushee, B. J., J. Kim-Gina, and E. Leung. 2020. Public and private information channels along supply chains: Evidence from contractual private forecasts. Working paper, University of Pennsylvania, University of California, Los Angeles and Erasmus University Rotterdam.

Cachon, G. P., and M. .Fisher. 2000. Supply chain inventory management and the value of shared information. *Management Science* 46, 1032–1048.

Carter, M. E., L. F. Lee and E. Yu. 2025. Real effects of proposed Scope 3 disclosures. Working paper, Boston College.

CDP. 2008. Global supply chain report. Available at https://www.fao.org/fileadmin/user_upload/rome2007/docs/Supply%20Chain%20Leadership%20Collaboration%20(SCLC)%20Pilot%20Results%20and%20Findings%20Report.pdf.

CDP. 2009. Global supply chain report. Available at https://www.groceryretailonline.com/doc/carbon-disclosure-project-supply-chain-report-0002.

CDP. 2010. Global supply chain report. Available at https://www.greenunivers.com/wp-content/uploads/2010/02/CDP-Supply-Chain-Report_20101.pdf.

CDP. 2014. Global supply chain report. Available at https://cdn.cdp.net/cdp-production/cms/reports/documents/000/000/633/original/CDP-Supply-Chain-Report-2014.pdf.

CDP. 2015. Global supply chain report. Available at https://www.supplychain247.com/paper/supply_chain_sustainability_revealed_a_country_comparison.

CDP. 2016. Global supply chain report. Available at https://www.cdp.net/en/research/global-reports/global-supply-chain-report-2016.

CDP. 2018. Global supply chain report. Available at https://cdn.cdp.net/cdp-production/cms/reports/documents/000/003/014/original/CDP_Supply_Chain_Report_2018.pdf?1518084325.

CDP. 2024. Strengthening the chain. Available at https://www.cdp.net/en/reports/downloads/7890.

Chen, Y.-C., M. Hung, and Y. Wang. 2018. The effect of mandatory CSR disclosure on firm profitability and social externalities: Evidence from China. *Journal of Accounting and Economics* 65, 169–190.

Chen, Y., G. Hu, J. Yao, and J. Zhao. 2022. Customer concentration and managerial bad news Withholding. *Journal of Accounting, Auditing & Finance* 39, 1–24.

Cho, S. Y., C. Lee, and R. J. Pfeiffer. 2013. Corporate social responsibility performance and information asymmetry. *Journal of Accounting and Public Policy* 32, 71–83.

Cho, Y. J., J. Kim, H. Yang, and M. Yang. 2023. Corporate disclosures for green supply chains: Evidence from Scope 3 emissions disclosure. Working paper, Singapore Management University.

Christensen, H. B., E. Floyd, L. Y. Liu, and M. Maffett. 2017. The real effects of mandated information on social responsibility in financial reports: Evidence from mine-safety records. *Journal of Accounting and Economics* 64, 284–304.

Christensen, H. B., L. Hale and C. Leuz. 2021. Mandatory CSR and sustainability reporting: Economic analysis and literature review. *Review of Accounting Studies* 26, 1176–1248.

Cohen, S., I. Kadach, and G. Ormazabal. 2023. Institutional investors, climate disclosure, and carbon emissions. *Journal of Accounting and Economics* 76, 101640.

Crawford, S., Y. Huang, N. Li, and Z. Yang. 2020. Customer concentration and public disclosure: Evidence from management earnings and sales forecasts. Contemporary Accounting Research 37, 131–159.

Dai, R., H. Liang, and L. Ng. 2021. Socially responsible corporate customers. *Journal of Financial Economics* 142, 598–626.

Darendeli, A., P. Fiechter, J.-M. Hitz, and N. Lehmann. 2022. The role of corporate social responsibility (CSR) information in supply-chain contracting: Evidence from the expansion of CSR rating coverage. *Journal of Accounting and Economics* 74, 101525.

Deng, J., M. Hung, and S. Wang. 2024. The Effect of Mandatory Carbon Disclosure Along Global Supply Chains. Working paper, Hong Kong University of Science and Technology.

Downar, B., J. Ernstberger, S. Reichelstein, S. Schwenen, and A. Zaklan. 2021. The impact of carbon disclosure mandates on emissions and financial operating performance. *Review of Accounting Studies* 26, 1137–1175.

Duguay, R., T. Rauter, and D. Samuels. 2023. The impact of open data on public procurement. *Journal of Accounting Research* 61, 1159–1224.

Ellis, J. A., C. E. Fee, and S. E. Thomas. 2012. Proprietary costs and the disclosure of information about customers. *Journal of Accounting Research* 50, 685–727.

FTSE Russell. 2024. Scope for improvement: Solving the Scope 3 conundrum. Available at https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.lseg.com/en/ftse-russell/research/solving-scope-3-conundrum&ved=2ahUKEwibxv-Dtr6MAxXUk1YBHdZEG5sQFnoECB0QAQ&usg=AOvV aw2cwWfRoMCOLgthAFgnxlJs.

GHG Protocol Initiative. 2013. Corporate value chain (Scope 3) accounting and reporting standard. Available at https://ghgprotocol.org/sites/default/files/standards/Corporate-Value-Chain-Accounting-Reporing-Standard_041613_2.pdf.

Gipper, B., F. Sequeira, and S.X., Shi. 2024. Carbon Accounting Quality: Measurement and the Role of Assurance. Working paper, Stanford University and University of Washington.

Goldstein, I., S. Yang, and L. Zuo. 2023. The real effects of modern information technologies: Evidence from the EDGAR implementation. *Journal of Accounting Research* 61, 1699–1733.

Greenstone, M., C. Leuz, and P. Breuer. 2023. Mandatory disclosure would reveal corporate carbon damages. *Science* 381, 837–840.

Grewal, J., E. J. Riedl, and G. Serafeim. 2019. Market Reaction to Mandatory Nonfinancial Disclosure. *Management Science* 65, 3061–3084.

Hainmueller, J. 2012. Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Political Analysis 20, 25–46.

Hales, J. 2023. Everything changes: A look at sustainable investing and disclosure over time and a discussion of "Institutional investors, climate disclosure, and carbon emissions." *Journal of Accounting and Economics* 72, 101645.

Healy, P. M., and K. G. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics* 31, 405–440.

Huang, J. and S. Lu. 2022. ESG Performance and Voluntary ESG Disclosure: Mind the (Gender Pay) Gap. Working paper, University of Texas at Dallas and Harvard University.

International Sustainability Standards Board (ISSB). 2022. Basis for conclusions on exposure draft IFRS S2 climate-related disclosures. Available athttps://www.ifrs.org/content/dam/ifrs/project/climate-related-disclosures/issb-exposure-draft-2022-2-basis-for-conclusions-climate-related-disclosures.pdf.

International Sustainability Standards Board (ISSB). 2023. IFRS S2 Climate-related Disclosures. Available at https://www.ifrs.org/issued-standards/ifrs-sustainability-standards-navigator/ifrs-s2-climate-related-disclosures/.

Jira, C., and M. W. Toffel. 2013. Engaging supply chains in climate change. *Manufacturing & Service Operations Management* 15, 559–77.

Krueger P., Z. Sautner, and L. T. Starks. 2020. The importance of climate risks for institutional investors. *The Review of Financial Studies* 33, 1067–1111.

Krueger P., Z. Sautner, D. Y. Tang, and R. Zhong. 2024. The effects of mandatory ESG disclosure around the world. *Journal of Accounting Research* 62, 1795–1847.

Lambert, R., C. Leuz, and R. E. Verrecchia. 2007. Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research* 45, 385–420.

Mahieux, L., H. Sapra and G. Zhang. 2025. Measuring greenhouse gas emissions: What are the costs and benefits? *Journal of Accounting Research*.

Matthews, H. S., C. T. Hendrickson, and C. L. Weber. 2008. The importance of carbon footprint estimation boundaries. Environmental Science & Technology 42, 5839–5842.

McClure, C., S. Shi, and E. Watts. 2025. Information acquisition costs and price informativeness: Global evidence. Working paper, University of Chicago, University of Washington and Yale University.

McMullin, J., and B. Schonberger. 2022. When good balance goes bad: A discussion of common pitfalls when using entropy balancing. *Journal of Financial Reporting* 7, 167–196.

Özer, Ö., Y. Zheng, and K. Chen. 2011. Trust in forecast information sharing. *Management Science* 57, 1 111–1137.

Patatoukas, P. N. 2012. Customer-base concentration: Implications for firm performance and capital markets. *The Accounting Review* 87, 363–392.

Reichelstein, S. 2024. Corporate carbon accounting: balance sheets and flow statements. *Review of Accounting Studies* 29, 2125–2156.

Schiller, C. 2018. Global supply-chain networks and corporate social responsibility. Working paper, Arizona State University.

Serafeim, G., and G. Vélez Caicedo, 2022. Machine learning models for prediction of Scope 3 carbon emissions. Working paper, Harvard University.

She, G. 2022. The real effects of mandatory nonfinancial disclosure: Evidence from supply chain transparency. *The Accounting Review* 97, 399–425.

Shi, Y., J. Wu, Y. Zhang, and Y. Zhou. 2023. Green image management in supply chains: Strategic disclosure of corporate suppliers. Working paper, The Chinese University of Hong Kong and Peking University.

Snam. 2015. Sustainable Paths. 2015 Report on Corporate Social Responsibility. Available at https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://www.snam.it/content/dam/snam/pages-attachments/en/governance/documents/storico-assemblee/2016/2015_report_on_corporate_social_responsibility.pdf&ved=2ahUKEwiYmNi33sSLAxUQbfUHHWGsGSwQFnoECBsQAQ&usg=AOvVaw2N3wfWnmPbXPiywSa9Oxfv.

Wang, L. L. 2023. Transmission effects of ESG disclosure regulations through bank lending networks. *Journal of Accounting Research* 61, 935–978.

World Economic Forum. 2023. Emissions measurement in supply chains: Business realities and challenges. Available at https://www.weforum.org/publications/emissions-measurement-in-supply-chains-business-realities-and-challenges.

Appendix A
Excerpts of the CDP climate change questionnaire supply chain module

This appendix contains excerpts from the 2018 CDP supply chain module questionnaires.

Supply chain introduction

(SC0.0) If you would like to do so, please provide a separate introduction to this module.

(SC0.1) What is your company's annual revenue for the stated reporting period?

(SC0.2) Do you have an ISIN for your company that you would be willing to share with CDP?

…

Section 1: Allocating your emissions to your customers

(SC1.1) Allocate your emissions to your customers listed below according to the goods or services you have sold them in this reporting period.

Please complete the following table. The table is displayed over several rows for readability. You are able to add rows by using the "Add Row" button at the bottom of the table.

Requesting member	**Scope of emissions**	**Emissions in metric tons of CO2e**	**Uncertainty (± %)**
[Drop-down menu of requesting members]	Select from: • Scope 1 • Scope 2 • Scope 3	Numerical field [enter a number from 0-999,999,999,999 using a maximum of 4 decimal places and no commas]	Percentage field [enter a percentage from 0-999,999 using a maximum of 4 decimal places and no commas]
Major sources of emissions	**Verified***	**Allocation method**	**Please explain how you have identified the GHG source…**
Text field [maximum 2,500 characters]	Select from: • Yes • No	Select from drop-down options below	Text field [maximum 5,000 characters]

…

Description of allocation method drop-down options (column 7). Select one of the following options:

• Allocation not necessary due to type of primary data available • Allocation not necessary as secondary data used • Allocation based on mass of products purchased • Allocation based on the volume of products purchased • Allocation based on the energy content of products purchased • Allocation based on the chemical content of products purchased	• Allocation based on the number of units purchased • Allocation based on area • Allocation based on another physical factor • Allocation based on the market value of products purchased • Other, please specify

(SC1.2) Where published information has been used in completing SC1.1, please provide a reference(s).

(SC1.3) What are the challenges in allocating emissions to different customers, and what would help you to overcome these challenges?

…

Section 2: Collaborative opportunities

(SC2.1) Please propose any mutually beneficial climate-related projects you could collaborate on with specific CDP supply chain members.

…

Section 3: Action exchange

(SC3.1) Do you want to enroll in the 2018-2019 CDP Action Exchange initiative?

…

Section 4: Product (goods and services) level data

(SC4.1a) Give the overall percentage of total emissions, for all Scopes, that are covered by these products.

(SC4.2a) Complete the following table for the goods/services for which you want to provide data.

Name of good/ service	**Description of good/ service**	**Type of product**	**SKU (Stock Keeping Unit)**
Text field [maximum 2,400 characters]	Text field [maximum 2,400 characters]	Select from: Final, Intermediate	Text field [maximum 50 characters]

Total emissions in kg CO2e per unit	**± % change from previous figure supplied**	**Date of previous figure supplied**	**Explanation of change**	**Methods used to estimate lifecycle emissions**
Numerical field	Numerical field		Text field [maximum 2,400 characters]	Select from: …

…

Appendix B
CDP-SC survey participation statistics

Year	# CDP-SC Customers	# Suppliers Requested	# Suppliers Responded	# Suppliers Publicized Response
2007	12	328	144	-
2008	34	2,318	634	-
2009	44	1,402	715	375
2010	57	1,853	1,000	659
2011	50	4,234	1,864	958
2012	54	6,215	2,415	1625
2013	64	5,624	2,868	1879
2014	66	6,503	3,396	2209
2015	75	7,800	4,005	2523
2016	89	8,200	4,300	2882
2017	99	9,139	4,800	1578
2018	115	11,692	5,600	2719
2019	125	13,111	6,958	3302

This appendix provides the annual statistics for the number of customer firms participating in the CDP-SC program, the number of suppliers requested to complete the survey, the number of suppliers that responded to the survey, and the number of suppliers that publicized responses. Information for the number of suppliers that publicized responses is not available for the years 2007 and 2008. 2007 is the year of the CDP-SC pilot program with relatively fewer participating customers and suppliers.

Appendix C
Propensity score matching for supplier samples

Panel A: Logit regression used to calculate the propensity score

Dep Var =	**Prob (Treat=1)**	
Sample =	**Pre-Match**	**Post-Match**
	(1)	(2)
Size	0.847***	0.024
	(0.010)	(0.041)
Leverage	0.517***	0.003
	(0.066)	(0.014)
ROA	2.085***	-0.163
	(0.142)	(0.200)
Sales Growth	-0.618***	-0.127
	(0.041)	(0.426)
Tangibility	-1.118***	-0.009
	(0.063)	(0.048)
R&D	8.719***	0.102
	(0.299)	(0.233)
TobinQ	-0.001	-0.348
	(0.005)	(0.789)
Ln(Scope1)	-0.011*	0.007
	(0.006)	(0.026)
Industry FE	Yes	Yes
#Firms	9,318	2,640
Pseudo R^2	0.226	0.004

Panel B: Statistics for firm characteristics before the event for the PSM sample

	Treatment		**Benchmark**		**Difference in Mean**	
	Mean	Median	Mean	Median	Treat. - Bench.	t-stats
Size	8.017	8.061	7.989	7.984	0.028	0.468
TobinQ	0.249	0.239	0.25	0.236	-0.001	-0.126
Leverage	0.052	0.047	0.052	0.044	0.000	0.044
ROA	0.150	0.066	0.143	0.069	0.007	0.240
Sales Growth	0.300	0.264	0.298	0.245	0.003	0.271
Tangibility	0.016	0.002	0.014	0.001	0.002	1.363
R&D	2.331	1.590	2.336	1.488	-0.006	-0.033
Ln(Scope 1)	11.348	11.105	11.284	10.841	0.065	0.551

Panel A reports the results of the logistic regressions for constructing the PSM sample, using the average value of firm characteristics during the [-3, -1] window. I use single nearest-neighbor propensity score matching without replacement within a caliper width of 0.05. ***, **, * represent the significance at the 1%, 5% and 10% two-tailed levels, respectively. Panel B compares the differences in firm characteristics between treatment and benchmark samples and their t-statistics.

Appendix D
Variable definitions

Variable	Definition
Dependent variables	
Ln(Scope 1)	The natural logarithm of Scope 1 emissions, where Scope 1 emissions are direct carbon emissions (in metric tons) stemming from sources controlled or owned by the firm.
Ln(Scope 1 Intensity)	The natural logarithm of Scope 1 intensity, where Scope 1 intensity is Scope 1 emissions scaled by revenue.
Emission Reduction Policy	Whether the supplier has any emission reduction policy in a firm-year.
Ln(Num Env Policy)	The natural logarithm of number of internal environmental policies.
Ln(Num Customer)	The natural logarithm of number of unique customers that a supplier has supply chain relationships with.
Ln(Num New Customer)	The natural logarithm of number of unique new customers that a supplier has supply chain relationships with.
Ln(Num Customers Disclose)	The natural logarithm of the number of customers identified in FactSet Revere Supply Chain data that disclosed relationships with a supplier during a year.
Upstream Scope 3 Disclosure	Binary variable that equals 1 if a firm discloses at least one category of upstream Scope 3 emissions to the CDP in a firm-year.
Category 1 Disclosure	Binary variable that equals 1 if a firm discloses Category 1 Scope 3 emissions (purchased goods and services) to the CDP in a firm-year.
Log(# Upstream Scope 3 Disclosure)	The natural logarithm of the number of upstream Scope 3 emission categories disclosed to the CDP in a firm-year.
Ave Usage Upstream Scope 3	The average percentage of emissions calculated using data obtained from suppliers or value chain partners across all the categories of upstream Scope 3 emissions in a firm-year.
Usage Category 1	The percentage of Category 1 Scope 3 emissions calculated using data obtained from suppliers or value chain partners in a firm-year.
Test variables	
Treat	Binary variable that equals 1 if a supplier has at least one customer which has adopted the CDP-SC program, and 0 otherwise.
Post	Binary variable that equals 1 since the earliest year a supplier's customer joined the CDP-SC program, and 0 otherwise. For

	suppliers omitted by FactSet, *Post* equals 1 starting from the earliest year of its response publication onwards and 0 otherwise.
Control variables	
Size	The natural logarithm of book value of assets at the end of a fiscal year (in millions of US dollars).
TobinQ	Total assets plus the market value of equity minus deferred taxes minus the book value of equity divided by total assets at the end of a fiscal year.
Leverage	Sum of long-term debt and short-term debt, scaled by total assets at the end of a fiscal year.
ROA	Earnings before extraordinary items scaled by the average total assets at the beginning and the end of a fiscal year.
Sales Growth	Percentage change in annual sales.
Tangibility	Net book value of property, plant, and equipment scaled by total assets at the end of a fiscal year.
R&D	Annual R&D expenditure scaled by total assets at the end of a fiscal year. Missing R&D expenditure is set to zero.
Mand. ESG	Binary variable that equals 1 if a firm-year's country adopted mandatory ESG disclosure regulations (Krueger et al. 2024).

Appendix E
Excerpts of Scope 3 emissions in the CDP climate change questionnaire

This appendix provides excerpts of Scope 3 emissions in the 2018 CDP climate change questionnaire.

14. Scope 3 Emissions

14.1 Please account for your organization's Scope 3 emissions, disclosing and explaining any exclusions

…

Sources of Scope 3 emissions	Evaluation Status	Metric tonnes CO2e	Emissions calculation methodology	Percentage of emissions calculated using data obtained from suppliers or value chain partners
Purchased goods and services				
Capital goods				
Fuel-and-energy-related activities (not included in Scope 1 or 2)				
Upstream transportation and distribution				
Waste generated in operations				
Business travel				
Employee commuting				
Upstream leased assets Investments				
Downstream transportation and distribution				
Processing of sold products Use of sold products				
End of life treatment of sold products				
Downstream leased assets Franchises				
Other (upstream)				
Other (downstream)				

Table 1
Sample distribution

Panel A: Sample selection procedure

	# CDP-SC Customer Firms	Treatment Sample		Benchmark Sample	
		# Firms	# Firm-years	# Firms	# Firm-years
- All CDP-SC participating customers	378	-	-	-	-
- Long-term customers	182	-	-	-	-
- Long-term customers' public suppliers in FactSet Supply Chain data and CDP Supply Chain climate change public spreadsheets 2003-2023	170	11,613	-	19,596	-
- After removing suppliers ended relationships with customers prior to joining year	-	9,801	-	-	-
- After removing non-top 100 suppliers	-	5,024	-	-	-
- After removing suppliers with event year after 2020	-	4,854	-	-	-
- After removing missing control variables for firm characteristics	-	4,596	72,704	18,081	231,206
- After removing missing Trucost carbon emissions data	-	3,757	44,115	8,110	62,779
- After removing missing NAICS2, financial firms (NAICS2=52), or public administration (NAICS2=92,99)	-	3,553	41,091	7,221	53,461
- After removing outliers in Scope 1 emissions, countries with 5 or fewer firms	-	3,525	40,392	7,157	52,228
Final EB samples (with observations present during both pre- and post-periods)	-	**2,161**	**18,380**	**7,157**	**52,228**
Final PSM samples (after propensity-score matching)	-	**1,431**	**11,850**	**1,209**	**11,147**

Table 1, Continued

Panel B: Sample distribution by year

Calendar Year	EB treatment Sample	EB Benchmark Sample	PSM Treatment Sample	PSM Benchmark Sample
	# Firm-years	# Firm-years	# Firm-years	# Firm-years
2003	110	240	49	27
2004	188	548	87	70
2005	304	797	154	124
2006	409	896	207	170
2007	589	941	303	258
2008	724	943	371	319
2009	865	1,059	441	397
2010	956	1,137	495	469
2011	1,098	1,187	579	529
2012	1,160	1,221	631	547
2013	1,248	1,439	732	630
2014	1,344	1,528	817	681
2015	1,356	1,635	857	725
2016	1,578	4,253	1,100	1,101
2017	1,437	4,712	1,041	1,048
2018	1,328	5,078	992	997
2019	1,169	5,321	909	909
2020	1,034	5,743	828	811
2021	869	5,948	724	713
2022	546	5,947	469	542
2023	68	1,655	64	80
Total	**18,380**	**52,228**	**11,850**	**11,147**

Table 1, Continued

Panel C: Sample distribution by economy

	EB Sample				PSM Sample			
	Treatment Sample		Benchmark Sample		Treatment Sample		Benchmark Sample	
	# Firms	# Firm-years	# Firms	# Firm-years	# Firms	# Firm-years	# Firms	# Firm-years
Argentina	1	4			1	4	1	10
Australia	34	276	222	1,823	27	219	32	313
Austria	8	76	8	101	6	59	5	45
Bahrain							1	9
Barbados			1	1				
Belgium	10	88	18	149	7	58	4	30
Bermuda	5	42	12	108	4	33	2	14
Brazil	54	455	48	305	41	338	9	82
British Virgin Islan			1	3				
Canada	52	429	216	1,679	36	292	28	313
Cayman Islands	4	34	5	40	3	28	1	9
Chile	20	177	6	76	18	158	1	10
China	125	898	1,425	9,382	98	690	299	2,664
Colombia	2	17	4	33	1	7		
Costa Rica			1	2				
Croatia							1	6
Cyprus	1	7			1	7	1	7
Denmark	19	166	16	111	7	58	4	49
Egypt	3	25	16	144	3	25	1	10
Faroe Islands			1	10				
Finland	21	187	23	146	14	124	2	20
France	92	797	91	486	46	385	10	74
Germany	69	606	71	530	37	314	17	182
Greece	5	35	17	135	4	25	2	19
Hong Kong	29	238	276	2,110	20	166	45	402
India	65	509	266	1,923	45	347	48	451
Indonesia	9	63	82	625	8	54	10	98
Ireland	15	135	13	84	10	93	2	14
Israel	13	91	46	328	10	70	10	100
Italy	19	167	59	471	15	127	20	183
Japan	291	2,484	1,125	8,750	186	1,486	200	1,869
Kazakhstan							1	9
Kenya							1	9

Table 1, Continued

Kuwait	1	6	10	49			2	11
Luxembourg	13	114	9	70	9	79	5	51
Macau	1	9	3	24	1	9		
Malaysia	8	73	110	848	7	64	15	114
Mauritius			1	2				
Mexico	17	144	23	238	13	111	8	61
Monaco			4	29			1	7
Mongolia			1	10				
Morocco							1	8
Netherlands	34	288	24	141	18	148	4	26
New Zealand	3	26	29	233	3	26	4	30
Nigeria	1	6	11	111	1	6	2	16
Norway	16	131	33	239	10	79	5	81
Pakistan	1	8	29	258	1	8	5	40
Peru	1	10	9	94	1	10	1	7
Philippines	5	43	31	286	5	43	3	47
Poland	4	34	38	324	2	17	4	39
Portugal	3	29	10	101	2	20	2	17
Qatar			11	90			1	8
Russian Federation	12	101	34	275	6	50	13	124
Saudi Arabia	2	12	52	261	2	12	3	14
Singapore	18	152	47	290	10	84	4	27
Slovenia							1	6
South Africa	21	191	56	658	20	183	8	89
South Korea	82	700	583	4,277	59	490	86	748
Spain	31	273	29	240	14	118	7	79
Sweden	35	315	87	520	23	203	13	112
Switzerland	42	369	52	432	26	223	13	140
Taiwan	83	695	430	3,164	53	443	61	538
Thailand	13	107	103	790	12	97	15	137
Turkey	8	68	48	330	8	68	2	9
Ukraine	1	10	1	13	1	10		
United Arab Emirates	4	28	13	86	3	19	2	15
United Kingdom	170	1,533	175	1,586	120	1,075	24	235
United States	564	4,892	984	6,541	353	2,988	135	1,303
Uruguay	1	7						
Vietnam			8	63				
Zimbabwe							1	7
Total	**2,161**	**18,380**	**7,157**	**52,228**	**1,431**	**11,850**	**1,209**	**11,147**

Table 1, Continued

Panel D: Sample distribution by industry

NAICS2 - industry description	EB Treatment		EB Benchmark		PSM Treatment		PSM Benchmark	
	# Firm-years	%	# Firm-years	%	# Firm-years	%	# Firm-years	%
11 - agriculture, forestry, fishing & hunting	33	0.18	351	0.67	33	0.28	6	0.05
21 - mining, quarrying, and oil land gas extraction	367	2.00	4,528	8.67	314	2.65	349	3.13
22 - utilities	834	4.54	2,737	5.24	656	5.54	685	6.15
23 - construction	507	2.76	1,949	3.73	393	3.32	450	4.04
31 - manufacturing-food, textile, apparel	1,520	8.27	3,631	6.95	1,037	8.75	931	8.35
32 - manufacturing-wood, paper, printing, petroleum, chemicals, plastics	3,152	17.15	9,520	18.23	2,115	17.85	1,826	16.38
33 - manufacturing-metals, machinery, computers, electrical, furniture	5,960	32.43	11,733	22.46	3,320	28.02	2,982	26.75
42 - wholesale trade	600	3.26	2,085	3.99	484	4.08	471	4.23
44 - retail trade-motor vehicles, furniture, electronics, food, gas	285	1.55	2,086	3.99	220	1.86	172	1.54
45 - retail trade-sporting goods, books, florists, office supplies, mail-order, vending	238	1.29	1,341	2.57	192	1.62	227	2.04
48 - transportation & warehousing-air transport, water transport, trucks, pipelines	689	3.75	2,366	4.53	609	5.14	528	4.74
49 - transportation & warehousing-post service, courier & express delivery service, local messengers, warehousing & storage	74	0.40	93	0.18	15	0.13	19	0.17
51 - information	2,015	10.96	3,533	6.76	1,173	9.90	1,111	9.97
53 - real estate & rental & leasing	269	1.46	878	1.68	171	1.44	186	1.67
54 - professional, scientific & technical services	1,130	6.15	1,684	3.22	554	4.68	551	4.94
56 - admin/support waste management/remediation	315	1.71	808	1.55	249	2.10	289	2.59
61 - educational services	25	0.14	287	0.55	25	0.21	22	0.20
62 - health care and social assistance	94	0.51	919	1.76	83	0.70	135	1.21
71 - arts, entertainment & recreation	34	0.18	507	0.97	33	0.28	55	0.49
72 - accommodation & food services	215	1.17	1,082	2.07	150	1.27	120	1.08
81 - other services (except public administration)	24	0.13	110	0.21	24	0.20	32	0.29
Total	**18,380**	**100**	**52,228**	**100**	**11,850**	**100**	**11,147**	**100**

This table presents the sample distribution for the EB and the PSM samples. Panel A lists the sample selection procedure. Panel B presents sample distribution by year. Panel C presents sample distribution by economy. Panel D presents sample distribution by the NAICS2 industry.

Table 2
Summary statistics

Panel A: EB Treatment and benchmark suppliers

	EB Treatment Firms (N = 18,380 firm-years)					Benchmark Firms (N = 52,228 firm-years, before balancing the covariates)	
	Pre-Period		Post-Period		Difference		
	Mean	Median	Mean	Median	Mean (Post - Pre)	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Scope 1	3,193,107.187	92,465.710	2,746,018.896	75,613.706	-447,088.291*	1,827,288.586	21,732.201
Ln(Scope 1)	11.633	11.435	11.358	11.233	-0.275***	539.494	24.294
Ln(Intensity 1)	3.396	3.095	3.146	2.853	-0.250***	3.757	3.190
Size	8.500	8.516	8.568	8.593	0.068**	6.999	6.979
Leverage	0.247	0.239	0.264	0.250	0.016***	0.232	0.206
ROA	0.050	0.046	0.043	0.043	-0.007***	0.031	0.040
Sales Growth	0.097	0.063	0.067	0.043	-0.030***	0.129	0.070
Tangibiltiy	0.279	0.236	0.271	0.226	-0.008**	0.326	0.281
R&D	0.022	0.004	0.023	0.005	0.001	0.016	0.000
TobinQ	2.276	1.592	2.482	1.675	0.206***	2.375	1.501

Panel B: PSM treatment suppliers (N = 11,850 firm-years)

	Pre-Period		Post-Period		Difference
	Mean	Median	Mean	Median	Mean (Post - Pre)
	(1)	(2)	(3)	(4)	(5)
Scope 1	2,492,886.365	77,655.136	2,109,984.604	62,165.709	-382,901.761*
Ln(Scope 1)	11.511	11.260	11.197	11.038	-0.314***
Ln(Intensity 1)	3.662	3.325	3.367	3.115	-0.295***
Size	8.088	8.124	8.168	8.199	0.080**
Leverage	0.251	0.242	0.270	0.258	0.019***
ROA	0.053	0.047	0.042	0.042	-0.011***
Sales Growth	0.129	0.065	0.086	0.046	-0.043*
Tangibiltiy	0.307	0.270	0.300	0.261	-0.007
R&D	0.015	0.001	0.016	0.002	0.001
TobinQ	2.589	1.568	2.729	1.618	0.140

Panel C: PSM benchmark suppliers (N = 11,147 firm-years)

	Pre-Period		Post-Period		Difference
	Mean	Median	Mean	Median	Mean (Post - Pre)
	(1)	(2)	(3)	(4)	(5)
Scope 1	4,295,831.123	57,065.356	4,260,231.289	45,391.059	-35,599.834
Ln(Scope 1)	11.433	10.952	11.123	10.723	-0.310***
Ln(Intensity 1)	3.824	3.259	3.533	3.073	-0.291***
Size	8.032	8.009	8.117	8.100	0.085**
Leverage	0.252	0.239	0.285	0.236	0.033*
ROA	0.055	0.045	0.035	0.036	-0.020***
Sales Growth	0.153	0.074	0.090	0.046	-0.063***
Tangibiltiy	0.311	0.265	0.289	0.230	-0.022***
R&D	0.012	0.000	0.016	0.002	0.004***
TobinQ	2.273	1.477	2.278	1.426	0.005

This table presents the descriptive statistics of the variables for regression analyses by EB and PSM samples. See Appendix D for variable definitions. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels.

Table 3
The effect of customer demand for carbon disclosures on suppliers

Panel A: Main analysis

Dep Var =	*Ln(Scope 1)*					
Sample =	EB			PSM		
	(1)	(2)	(3)	(4)	(5)	(6)
Treat×Post	**-0.067****	**-0.080*****		**-0.061***	**-0.069****	
	(0.029)	**(0.022)**		**(0.036)**	**(0.027)**	
Treat	-0.029			0.113**		
	(0.053)			(0.057)		
Post				-0.225***		
				(0.029)		
Treat×Year - 5			0.052			0.061
			(0.033)			(0.040)
Treat×Year - 4			0.047*			0.066*
			(0.026)			(0.035)
Treat×Year - 3			0.011			0.009
			(0.020)			(0.028)
Treat×Year - 2			-0.001			-0.001
			(0.013)			(0.020)
Treat×Year 0			**-0.023***			-0.010
			(0.013)			(0.016)
Treat×Year 1			**-0.054*****			**-0.046***
			(0.019)			**(0.024)**
Treat×Year 2			**-0.077*****			**-0.065****
			(0.024)			**(0.031)**
Treat×Year 3			**-0.099*****			**-0.071***
			(0.029)			**(0.036)**
Treat×Year 4			**-0.088****			**-0.083****
			(0.035)			**(0.040)**
Size	0.953***	0.717***	0.695***	1.025***	0.639***	0.670***
	(0.018)	(0.029)	(0.030)	(0.023)	(0.033)	(0.034)
Leverage	-0.216	-0.304***	-0.324***	-0.018	-0.220*	0.026*
	(0.143)	(0.111)	(0.125)	(0.186)	(0.120)	(0.015)
ROA	1.646***	0.692***	0.693***	2.656***	0.695***	0.386***
	(0.267)	(0.114)	(0.129)	(0.314)	(0.144)	(0.115)
Sales Growth	0.014	0.118***	0.093***	-0.024	0.138***	0.003
	(0.045)	(0.023)	(0.022)	(0.063)	(0.026)	(0.008)
Tangibility	2.531***	0.349**	0.299**	2.269***	0.235	0.135
	(0.153)	(0.152)	(0.149)	(0.211)	(0.169)	(0.159)
R&D	-3.104***	3.973***	4.089***	-3.847***	4.722***	1.371***
	(0.766)	(0.689)	(0.754)	(1.067)	(0.920)	(0.470)
TobinQ	-0.063***	-0.001	0.002	-0.079***	-0.011*	-0.000
	(0.008)	(0.006)	(0.006)	(0.011)	(0.006)	(0.001)
#Firm-years	70,608	70,608	70,608	22,997	22,997	22,997
Adj. R^2	0.738	0.949	0.95	0.737	0.963	0.963
Industry FE	Yes	No	No	Yes	No	No
Year FE	Yes	Yes	Yes	No	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes

This panel presents the regression results that examine the impact of customer demand for GHG information (reflected by adoption of the CDP-SC program) on suppliers' Scope 1 emissions. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for variable definitions. Standard errors are clustered by firm and reported in parentheses. *, **, *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 3, Continued

Panel B: Robustness tests

Dep Var =	*Ln(Scope 1)*						*Ln(Scope 1 Intensity)*	
Specification =	**Remove Suppliers in the CDP-Investor Program**		**Remove Suppliers Omitted by FactSet**		**All Suppliers**		**Alternative Measure**	
Sample =	EB	PSM	EB	PSM	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat×Post	**-0.085***** **(0.022)**	**-0.092***** **(0.031)**	**-0.074***** **(0.023)**	**-0.098***** **(0.029)**	**-0.031*** **(0.018)**	**-0.049**** **(0.020)**	**-0.069***** **(0.021)**	**-0.067**** **(0.027)**
#Firm-years	66,727	24,537	66,681	18,692	74,550	33,593	70,608	22,997
Adj. R^2	0.949	0.952	0.951	0.963	0.95	0.95	0.923	0.935
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This panel presents robustness tests for the main analysis in Table 3 Panel A. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for variable definitions. Columns (1) to (6) use alternative supplier samples. Columns (7) to (8) use the natural logarithm of Scope 1 intensity as the dependent variable. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 4
Cross-sectional analyses

Panel A: Analysis of CDP-SC customers' incentives

Dep Var =	***Ln(Scope 1)***					
Partition Var =	**Emissions Performance before Joining CDP-SC**		**Customers' Usage of Supplier GHG Information**		**Premium CDP-SC Member**	
Sample =	EB	PSM	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Treat×Post×Low Incentive (β1)	**-0.047***	**-0.084*****	-0.047	**-0.135****	**-0.049***	**-0.093*****
	(0.027)	**(0.032)**	(0.046)	**(0.059)**	**(0.026)**	**(0.032)**
Treat×Post×High Incentive (β2)	**-0.113*****	**-0.122*****	**-0.189*****	**-0.248*****	**-0.137*****	**-0.110****
	(0.034)	**(0.041)**	**(0.059)**	**(0.077)**	**(0.039)**	**(0.044)**
Difference (β2-β1)	***-0.066****	*-0.038*	***-0.142*****	*-0.113*	***-0.088*****	*-0.017*
Test of difference (t-statistics)	***(1.731)***	*(0.888)*	***(2.294)***	*(1.399)*	***(2.115)***	*(0.380)*
#Firm-years	66,681	18,692	41,265	4,499	66,681	18,692
Adj. R^2	0.951	0.963	0.957	0.967	0.951	0.963
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4, Continued

Panel B: Analysis of suppliers' incentives

Dep Var =	*Ln(Scope 1)*					
Partition Var =	**Whether Suppliers Publicize Responses**		**Emissions Performance in the Pre-Period**		**Country Environment Regulation and Enforcement**	
Sample =	EB	PSM	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)	(5)	(6)
Treat×Post×Low Incentive (β1)	-0.034	-0.046	-0.012	-0.031	0.002	0.003
	(0.028)	(0.033)	(0.028)	(0.032)	(0.041)	(0.043)
Treat×Post×High Incentive (β2)	**-0.113*****	**-0.100*****	**-0.125*****	**-0.115*****	**-0.107*****	**-0.099*****
	(0.028)	**(0.034)**	**(0.031)**	**(0.034)**	**(0.024)**	**(0.030)**
Difference (β2-β1)	***-0.079*****	*-0.054*	***-0.113******	***-0.084*****	***-0.109*****	***-0.102*****
Test of difference (t-statistics)	***(2.325)***	*(1.443)*	***(3.072)***	***(2.264)***	***(2.521)***	***(2.338)***
#Firm-years	70,608	22,997	70,608	22,997	70,608	22,997
Adj. R^2	0.949	0.961	0.949	0.961	0.949	0.961
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 4, Continued

Panel C: Analysis of suppliers' bargaining power

Dep Var =	*Ln(Scope 1)*			
Partition Var =	**Number of CDP-SC Customers**		**Relationship Duration with CDP-SC Customers**	
Sample =	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)
Treat×Post×Strong Bargain (β1)	-0.042	**-0.080****	**-0.072***	0.034
	(0.027)	**(0.031)**	**(0.041)**	(0.043)
Treat×Post×Weak Bargain (β2)	**-0.127*****	**-0.144*****	**-0.079***	**-0.086***
	(0.034)	**(0.046)**	**(0.041)**	**(0.047)**
Difference (β2-β1)	***-0.085*****	*-0.064*	*-0.007*	***-0.120*****
Test of difference (t-statistics)	***(2.241)***	*(1.377)*	*(0.132)*	*(2.010)*
#Firm-years	66,681	18,692	66,681	18,692
Adj. R^2	0.951	0.963	0.951	0.963
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 4, Continued

Panel D: Analysis of information asymmetry between suppliers and customers

Dep Var =	***Ln(Scope 1)***	
Partition Var =	**Suppliers' Voluntary Disclosure of Scope 1 Emissions**	
Sample =	EB	PSM
	(1)	(2)
Treat×Post×Low Information Asymmetry (β1)	**-0.061****	-0.037
	(0.026)	(0.032)
Treat×Post×High Information Asymmetry (β2)	**-0.102*****	**-0.107*****
	(0.030)	**(0.035)**
Difference (β2-β1)	*-0.041*	***-0.070****
Test of difference (t-statistics)	*(1.197)*	***(1.894)***
#Firm-years	70,608	22,997
Adj. R^2	0.949	0.961
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes

This table compares the cross-sectional differences in the reduction of Scope 1 emissions following the event. Panels A-D present cross-sectional regression results conditional on suppliers' incentives, customers' incentives, suppliers' bargaining power, and information asymmetry between suppliers and customers. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for variable definitions. All the regressions control for firm characteristics and include firm- and year- fixed effects. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 5
The effect of customer demand for carbon disclosures on suppliers' practice

Dep Var =	***Emission Reduction Policy***		***Ln(Num Env Policy)***	
Sample =	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)
Treat*Post	**0.006***	0.006	**0.024****	0.002
	(0.003)	(0.007)	**(0.012)**	(0.006)
Size	0.041***	-0.001	0.139***	0.003
	(0.006)	(0.023)	(0.021)	(0.018)
Leverage	-0.068***	0.001	-0.229***	0.033
	(0.021)	(0.071)	(0.071)	(0.069)
ROA	-0.036	-0.081	-0.151	-0.068
	(0.030)	(0.061)	(0.101)	(0.042)
Sales Growth	-0.003	-0.000	-0.010	-0.001
	(0.006)	(0.000)	(0.020)	(0.000)
Tangibility	0.007	-0.065	0.034	-0.090
	(0.021)	(0.075)	(0.074)	(0.079)
R&D	0.363**	-0.154	1.345**	-0.056
	(0.169)	(0.162)	(0.578)	(0.117)
TobinQ	0.003**	-0.000	0.009**	0.000
	(0.001)	(0.000)	(0.005)	(0.000)
#Firm-years	22,550	9,254	22,550	9,277
Adj. R^2	0.454	0.834	0.499	0.806
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

This table presents changes in suppliers' practices. The dependent variables are *Emission Reduction Policy* and *Ln(Num Env Policy)*. *Emission Reduction Policy* is a binary variable that equals 1 if a supplier has emission reduction policies in a firm-year. *Ln(Num Env Policy)* is the natural logarithm of the number of environmental policies in a firm-year. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for variable definitions. All the regressions control for firm characteristics and include firm- and year- fixed effects. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 6
The effect of customer demand for carbon disclosures on suppliers' supply-chain network

Dep Var =	***Ln(Num Customer)***		***Ln(Num New Customer)***	
Sample =	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)
Treat×Post	**0.554*****	**0.562*****	**0.325*****	**0.276*****
	(0.034)	**(0.044)**	**(0.032)**	**(0.038)**
Size	0.129***	0.172***	0.129***	0.086**
	(0.034)	(0.044)	(0.038)	(0.036)
Leverage	-0.183	-0.015	-0.322**	-0.002
	(0.127)	(0.010)	(0.131)	(0.010)
ROA	-0.208	-0.124	-0.031	-0.088
	(0.128)	(0.096)	(0.146)	(0.091)
Sales Growth	-0.086***	-0.010**	0.020	-0.006
	(0.024)	(0.005)	(0.037)	(0.005)
Tangibility	0.304	0.036	0.191	-0.112
	(0.207)	(0.168)	(0.179)	(0.158)
R&D	-0.290	0.192	0.067	-0.053
	(0.863)	(0.414)	(0.801)	(0.352)
TobinQ	0.002	0.001	0.000	0.000
	(0.008)	(0.000)	(0.007)	(0.001)
#Firm-years	46,263	15,645	46,263	15,645
Adj. R^2	0.780	0.750	0.401	0.359
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

This table presents regression analysis on changes in suppliers' supply chain network. The dependent variables are *Ln(Num Customer)* and *Ln(Num New Customer)*. *Ln(Num Customer)* is the natural logarithm of the number of customers that a supplier has in a firm-year, and *Ln(Num New Customer)* is the natural logarithm of new customers that a supplier has in a firm-year. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for definitions of additional variables. All the regressions include firm- and year- fixed effects. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 7
The effect of customer demand for carbon disclosures on customers' disclosure strategy

Dep Var =	***Ln(Num Customers Disclose)***		***Ln(Num Customers Disclose)***	
Sample =	EB	PSM	EB	PSM
	(1)	(2)	(3)	(4)
Treat×Post	**0.129*****	**0.117*****		
	(0.024)	**(0.030)**		
Treat×Post×More Emi. Reductions (β1)			**0.144*****	**0.120*****
			(0.028)	**(0.036)**
Treat×Post×Less Emi. Reductions (β2)			**0.091*****	**0.094*****
			(0.029)	**(0.035)**
Size	0.204***	0.187***	0.206***	0.172***
	(0.029)	(0.038)	(0.029)	(0.035)
Leverage	-0.192**	0.009	-0.199**	0.009
	(0.093)	(0.006)	(0.091)	(0.006)
ROA	-0.026	-0.037	-0.038	-0.021
	(0.095)	(0.065)	(0.093)	(0.060)
Sales Growth	-0.075***	-0.005	-0.074***	-0.005
	(0.016)	(0.003)	(0.016)	(0.003)
Tangibility	0.097	0.052	0.069	0.068
	(0.110)	(0.134)	(0.108)	(0.131)
R&D	-0.081	0.189	-0.162	0.177
	(0.484)	(0.189)	(0.474)	(0.184)
TobinQ	-0.001	-0.000	-0.002	-0.000
	(0.006)	(0.000)	(0.006)	(0.000)
Difference (β1-β2)			***0.053****	*0.026*
Test of difference (p-value)			*(0.075)*	*(0.494)*
#Firm-years	44,998	14,666	44,998	14,666
Adj. R^2	0.852	0.792	0.846	0.784
Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

This table presents changes in customers' disclosure strategy of supply-chain relationships. The dependent variable is *Ln(Num Customers Disclose)*, which is the natural logarithm of the number of customers that disclosed relationships with a sample supplier during a year. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for definitions of additional variables. All the regressions include firm- and year- fixed effects. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.

Table 8
The effect of customer demand for carbon disclosures on customers' Scope 3 disclosures

Dep Var =	***Upstream Scope 3 Disc***	***Category 1 Disc***	***Ln(# Upstream Scope 3 Disc)***	***Ave Usage Upstream Scope 3***	***Usage Category 1***
	(1)	(2)	(3)	(4)	(5)
Treat×Post	**0.090****	**0.084*****	**0.170*****	**0.271****	**0.196****
	(0.039)	**(0.031)**	**(0.063)**	**(0.135)**	**(0.093)**
Size	-0.034	-0.049	-0.069	-0.167	-0.136*
	(0.035)	(0.030)	(0.059)	(0.127)	(0.082)
Leverage	0.122	-0.317	-0.404	-0.989	0.553
	(0.308)	(0.422)	(0.767)	(1.862)	(0.611)
ROA	0.391	0.126	0.759	0.246	1.344
	(0.461)	(0.755)	(1.230)	(3.520)	(1.317)
Sales Growth	-0.094	0.075	0.031	0.427	-0.165
	(0.086)	(0.145)	(0.239)	(0.631)	(0.153)
Tangibility	0.255	0.185	0.587	2.364	1.714
	(0.384)	(0.598)	(0.940)	(2.841)	(1.477)
R&D	-6.973**	-7.942**	-14.094**	-27.822*	-6.821**
	(3.233)	(3.815)	(6.932)	(15.099)	(3.363)
TobinQ	0.025**	0.022	0.044	0.155	0.055
	(0.013)	(0.022)	(0.033)	(0.101)	(0.038)
Mand. ESG	-0.084	0.107	0.060	0.394	-0.288
	(0.059)	(0.089)	(0.170)	(0.418)	(0.184)
#Firm-years	3,334	3,334	3,334	3,334	3,334
Adj. R^2	0.598	0.541	0.614	0.527	0.441
Year FE	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes

This table presents changes in CDP-SC customers' Scope 3 disclosures. The dependent variables include: *Upstream Scope 3 Disc*, a binary variable that equals 1 if a supplier discloses at least one category of upstream Scope 3 emissions to the CDP; *Category 1 Disc*, a binary variable that equals 1 if a supplier discloses Category 1 Scope 3 emissions (purchased goods and services emissions); *Ln(# Upstream Scope 3 Disc)*, the natural logarithm of the number of disclosed upstream Scope 3 categories; *Average Usage Upstream Scope 3*, the average percentage of emissions calculated using data from suppliers across all upstream categories; *Usage Category 1*, the percentage of Category 1 Scope 3 emissions calculated using data from suppliers. *Treat* is a binary variable that equals 1 if a supplier has at least one customer which has adopted the program. *Post* is a binary variable that equals 1 starting from the earliest year a supplier's customer joined the program. See Appendix D for definitions of additional variables. All the regressions include firm- and year- fixed effects. Standard errors are clustered by firm and reported in parentheses. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 two-tailed levels, respectively.