Rewiring Supply Chains Through Climate Policy*

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July 29, 2024

Abstract

We show that climate transition risks can have a significant effect on supply chains. We find that suppliers exposed to the California cap-and-trade program are more likely to lose customer relationships and less likely to establish new ones. These supply chain adjustments are driven by a loss of competitiveness due to the program, as the effects are more pronounced when suppliers face more competitive pressure and produce less specific inputs. This rewiring of supply chains is consistent with carbon leakage as customers exposed to the program through production networks experience increased scope 3 emissions.

JEL classification: G32, Q54, Q55
Keywords: Climate finance, Carbon policy, Carbon emissions, Supply chain, Product market competition, Input specificity

*The authors gratefully acknowledge financial support from the Georg und Bertha Schwyzer-Winiker-Stiftung and the SNSF Grant Nr. 100018 204561 / 1 (project corporate short-termism). This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank.

1 Introduction

On their path to a low-carbon economy, many governments have adopted carbon pricing programs to curb emissions, leading to a patchwork of climate regulations across different countries and regions. Previous studies have documented that such uncoordinated climate policies and regulations can lead to carbon leakage as firms shift production and emissions from facilities in regions with regulated (higher) carbon prices to those with unregulated (lower) carbon prices (Ben-David, Jang, Kleimeier, and Viehs, 2021; Bartram, Hou, and Kim, 2022). In addition, carbon pricing can increase the costs of producing goods for regulated (local) firms, placing unregulated (foreign) competitors at a comparative advantage (Cosbey, Droege, Fischer, and Munnings, 2019). This competitiveness channel of carbon leakage can prompt customers to shift their sourcing to unregulated foreign suppliers, leading to far-reaching implications for trade flows and economic activity in the regions subject to the policies and for the regulation of emissions produced along the supply chain.

In this paper, we empirically test for the competitiveness channel of carbon leakage by investigating how carbon pricing policies affect supply chains. We examine whether suppliers experience the termination of their customer relationships as they compete with firms in regions without environmental policies in place. In addition, we examine how carbon pricing policies affect firms' financial performance, as well as environmental performance, by focusing on scope 3 carbon emissions.

It is ex-ante unclear whether heterogeneous carbon pricing policies would lead to the termination of supply chain relationships. On the one hand, the higher carbon price is a permanent shock to the affected firms' input costs (Ryan, 2012), placing them at a disadvantage relative to their competitors.[1] The introduction of environmental policies exposes firms

[1]For instance, in its SEC filings, Air Products and Chemicals Inc. states that "Any legislation that limits or taxes GHG emissions could impact the Company's growth, increase its operating costs, or reduce demand for certain of its products" Air Products and Chemicals Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/2969/000119312512476878/d409668d10k.htm.

to higher climate transition risks (Greenstone, 2002) When these risks affect suppliers, they increase supply chain risks arising from supply disruptions.[2] On the other hand, regulators actively reduce the impact of environmental policies on firms' competitiveness by providing exemptions to highly energy-intensive and trade-exposed sectors (Fowlie, Reguant, and Ryan, 2016). Moreover, high switching costs – such as those associated with search efforts or input specificity (Barrot and Sauvagnat, 2016; Bernard, Moxnes, and Saito, 2019) – along with the anticipation of future supply chain emission regulations (Ramadorai and Zeni, 2024), or pressure from environmentally conscious stakeholders and consumers (Aghion, Bénabou, Martin, and Roulet, 2020; Krueger, Sautner, and Starks, 2020) may mitigate the impact of carbon policies on firm competitiveness and consequently on supply chain relationships.

To disentangle these effects, we focus on suppliers exposed to the California cap-and-trade program, the second-largest cap-and-trade program worldwide, and the only carbon pricing policy regulating industrial firms' emissions in the United States. This program, introduced in 2013, imposes a cap on emissions of firms producing more than 25 thousand tons of carbon dioxide equivalents in their California plants. California offers an ideal setting to study the competitiveness channel for carbon programs, as other U.S. states do not regulate firms' emissions, providing us with a unique setup with within-country policy heterogeneity. This feature allows us to study whether customers terminate/maintain relationships with suppliers subject to the cap-and-trade program while engaging in new relationships with similar suppliers not subject to the program.

We use a difference-in-differences (DiD) methodology, combined with a matching approach, to analyze changes in the probability of terminating an existing relationship or initi-

[2] For instance, in its SEC filings, Campbell Soup Company mentions that "Increased compliance costs and expenses due to the impacts of climate change and additional legal or regulatory requirements regarding climate change that are designed to reduce or mitigate the effects of carbon dioxide and other greenhouse gas emissions on the environment may cause disruptions in, or an increase in the costs associated with, the running of our manufacturing facilities and our business, as well as increase distribution and supply chain costs." Campbell Soup Company, Form 10-K https://www.sec.gov/Archives/edgar/data/16732/000001673223000109/cpb-20230730.htm.

ating a new relationship with a supplier exposed to the cap-and-trade program. We exploit the introduction of the California cap-and-trade as a shock to the marginal costs of suppliers with polluting operations in California. To identify suppliers subject to the program (treated suppliers), we combine establishment-level emissions data from the U.S. Environmental Protection Agency (EPA) with supplier-customer relationship data from FactSet Revere. Our baseline matching approach ensures that treated suppliers are compared to a control sample of otherwise similar suppliers in terms of industry, location, size, and profitability. In addition, we use supplier-client pairs to compare the likelihood that the same customer terminates its link to a treated supplier relative to an otherwise similar control supplier in the same year. Our estimates include client-by-time fixed effects to absorb unobserved heterogeneity arising from the demand for the firms' products. Given our identification strategy, our estimates can be attributed to supply-side factors.

Our baseline results show that treated suppliers experience a 2.5 to 6.1 percentage point increase in the probability of terminating their pre-existing relationships with customers after the introduction of the cap-and-trade program. These results are economically meaningful, representing a 12% to 29% higher probability of terminating a relationship with suppliers subject to the program (evaluated at the unconditional probability of 21%). These results suggest that firms subject to the carbon pricing program suffer a loss of competitiveness vis-a-vis their competitors.

One concern with our interpretation of the results is that the higher probability of terminating a relationship with suppliers subject to the California cap-and-trade might be solely driven by a reshuffle in their customer base. For instance, Bartram et al. (2022) show that financially constrained suppliers shift their activity to their plants located in other states; this move might naturally lead them to begin relationships with new customers located in the proximity of their non-Californian plants. However, we find that our baseline results are both economically and statistically significant in the sub-sample of the suppliers that operate exclusively in California and in the sub-sample of non-financially constrained suppliers.

We also find that after the introduction of the carbon program, the probability of initiating a new relationship with a supplier exposed to the cap-and-trade is up to 10 percentage points lower relative to otherwise similar control suppliers. These findings imply that our baseline results are not solely driven by an adjustment of affected suppliers' customer base. Rather, the entire supply chain is rewired to reduce the business exposure to increasing climate transition risks.

We next test whether the competitiveness channel of carbon leakage drives our results. A prediction of this channel is that the effects should be stronger for firms operating in more competitive industries: customers can more easily shield themselves from climate transition risk-induced supply chain uncertainty by cutting ties with suppliers that operate in industries characterized by many highly substitutable producers. In line with this idea, we find that our baseline effects are more pronounced in the sub-samples of suppliers operating in industries characterized by lower market concentration, as proxied by a low Herfindahl-Hirschman Index (HHI), lower Lerner Index, and less concentrated groups of competitors. Similarly, we expect customers facing low switching costs to find it easier and less costly to source their inputs elsewhere. Indeed, we find that our effects are concentrated among suppliers selling less specialized goods and those with lower investments in R&D. In addition, results are stronger among suppliers with weaker ties to their customers, as measured by higher geographical distance and lower relationship duration.

To further corroborate the economic mechanism underlying our results, we examine the firm-level implications of the competitiveness channel of carbon leakage. This channel predicts that the program's introduction should place treated suppliers at a disadvantage relative to their competitors, due to the higher exposure to climate transition risks. In line with this prediction and consistent with the rewiring of supply chains away from the cap-and-trade program, we find that treated suppliers experience a higher drop in assets, revenues, and profitability, as well as a higher increase in costs of goods sold (COGS) relative to otherwise similar control suppliers.[3] In addition, we find that the deterioration of financial performance is greater for suppliers producing standardized inputs. In line with Greenstone (2002) and Ryan (2012), these results are consistent with a higher probability of disruptions in firms producing standardized inputs, which might provide incentives for customers to switch to avoid the propagation of the climate transition shock.

We then explore whether customers' anticipation of future environmental regulations outside of California might mitigate the observed effects (regardless of financial considerations). In line with this idea, we find that customers headquartered in jurisdictions characterized by higher environmental awareness – such as Democrat states and states that become members of the U.S. Climate Alliance at its onset – are less likely to terminate their relationships with suppliers subject to the cap-and-trade program.[4] Similarly, customers reporting relatively high attention to climate transition risks in the pre-treatment period (as measured using the index in Sautner, Van Lent, Vilkov, and Zhang, 2023) are less likely to terminate relationships with suppliers subject to the program.

Finally, we explore the environmental implications of our findings. We find that the introduction of the California cap-and-trade is not followed by a significant reduction in affected suppliers' U.S. total emissions and emission intensity (ratio of emissions to assets). Moreover, in line with the competitiveness channel for carbon leakage, we find that customers' emissions along the supply chain increase. Using several indicators obtained from different data sources to overcome the limitations of commonly used scope 3 emissions data (such as scarce quality

[3]In its SEC filings, United States Steel Corporation explicitly addresses the heterogeneity in environmental policies as a source of disadvantage "International environmental requirements vary. While standards in the EU, Canada, and Japan are generally comparable to U.S. standards, other nations, particularly China, have substantially lesser requirements that may give competitors in such nations a competitive advantage [...] GHG policies could negatively affect our results of operations and cash flows", United States Steel Corporation, Form 10-K https://www.sec.gov/Archives/edgar/data/1163302/000119312513061613/d448577d10k.htm.

[4]The U.S. Climate Alliance is a coalition that targets the transition to net zero through environmental awareness and climate action. It was created in 2017 by the initiative of governors of the states of California, Washington, and New York.

and availability), we show that the scope 3 emissions of firms that source products from at least one treated supplier increase following the introduction of the cap-and-trade program. These findings provide evidence of the unintended consequences of the California cap-and-trade program, in line with the most prominent carbon leakage mechanisms described by Cosbey, Droege, Fischer, and Munnings (2019).

Our paper contributes to several strands of the literature. First, our study speaks to the body of research on carbon leakage. Empirical studies suggest that the heterogeneity in climate policies may provide incentives to pollute outside of regions affected by the policies (Ivanov, Kruttli, and Watugala, 2023; Benincasa, Kabas, and Ongena, 2022; Laeven and Popov, 2023; Duchin, Gao, and Xu, 2022). Related to our work, Ben-David et al. (2021) and Bartram et al. (2022) find evidence of a within-firm reallocation of production to facilities outside of carbon jurisdictions. Our paper adds to this literature by revealing a different channel of carbon leakage that leads to a supply chain reconfiguration and by uncovering unintended financial and environmental consequences of this leakage.

Second, our paper contributes to the literature on the effects of shocks on production networks (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Carvalho, Nirei, Saito, and Tahbaz-Salehi, 2021; Jiang, Rigobon, and Rigobon, 2021; Baldwin and Freeman, 2022; Acemoglu and Tahbaz-Salehi, 2023). In particular, previous research shows that corporate social responsibility (CSR) and environmental, social, and governance (ESG) shocks propagate along the supply chain (Schiller, 2018; Dai, Liang, and Ng, 2021b; Bisetti, She, and Zaldokas, 2023; Homroy and Rauf, 2024). In addition, firms' environmental practices affect their supply chains (Dai, Duan, Liang, and Ng, 2021a; Asgharian, Dzieliński, Hashemzadeh, and Liu, 2023; Hege, Li, and Zhang, 2023).

Our paper is closely related to research on the effects of physical climate risk on supply chains (Barrot and Sauvagnat, 2016; Pankratz and Schiller, 2023). Specifically, Pankratz and Schiller (2023) show that suppliers exposed to heat days above expectations experience a higher probability of experiencing the termination of their customer relationships. Our paper differs by focusing on climate *transition* risks, and in particular, on state-wide environmental policies. This allows us to analyze the phenomenon of carbon leakage and uncover the policy's unintended environmental consequences. Contrary to physical climate risks or ESG shocks, the environmental policies we study represent a permanent and stronger shock to firms' production processes.

Finally, we add to the literature that examines how climate regulations trigger changes in firms' performance, behavior, and production processes (Greenstone, 2002; Ryan, 2012; Bushnell, Chong, and Mansur, 2013; Chan, Li, and Zhang, 2013; Dechezleprêtre and Sato, 2017; De Jonghe, Mulier, and Schepens, 2020; Bolton, Lam, and Muûls, 2023; Martinsson, Sajtos, Strömberg, and Thomann, 2024). Our paper shows that carbon pricing programs can not only affect firms' performance but also lead to a rewiring of production networks away from the program.

2 Background

2.1 Conceptual framework

There is wide agreement among economists that the most effective way to reduce worldwide carbon emissions is by imposing carbon pricing mechanisms. Thus, many jurisdictions have established carbon taxes or cap-and-trade systems to encourage a transition to a low-carbon economy. However, the decision to implement such policies is influenced by the unique economic, political, social, and environmental contexts of each jurisdiction, leading to large heterogeneity in the adoption of such policies across different regions and countries. The resulting landscape of carbon policies with partial geographical coverage provides plenty of scope for shifting pollution from high- to low-carbon pricing regimes. This phenomenon has been termed "carbon leakage".

The literature has identified a set of carbon leakage channels (Cosbey et al., 2019). Among them, the *competitiveness channel* has already been put forward in literature (see e.g., the comprehensive review by Fowlie et al., 2016). According to this mechanism, high carbon prices increase production costs in jurisdictions with environmental policies in place, leading to a drop in the competitiveness of the affected producers and to a comparative advantage for firms elsewhere. Downstream customers and final consumers respond to the reduced competitiveness and the potential ensuing supply chain uncertainty by shifting their sourcing to suppliers not subject to environmental policies. Within the context of the California cap-and-trade policy, Fowlie et al. (2016) estimate the risk of carbon leakage from California to international trade flows in the presence of an incomplete environmental policy affecting energy prices in California. This risk is significant in some industrial sectors with high energy intensity and trade exposure. Accordingly, to address carbon leakage concerns, the program exempts particularly exposed entities from part of the costs of the policy, and a large body of literature analyzes the possible impact of border carbon adjustment mechanisms aimed at leveling the competition between firms subject to heterogeneous environmental policies (Fowlie, Petersen, and Reguant, 2021).

Within this conceptual framework, we conduct an empirical study at the supply chain level. We focus on the competitiveness channel of carbon leakage by exploiting data on supply chains to study the effects of the introduction of a cap-and-trade program in California on the likelihood that firms affected by the program lose their customers to outside competitors and establish new relationships.

2.2 The California cap-and-trade program

With the 2006 Assembly Bill 32, California set the goal to transition to a low-carbon economy by committing to returning to 1990 emission levels by 2020. Framed within this goal, the California cap-and-trade program became effective in January 2013. During phase 1, between 2013 and 2014, the policy targeted electricity generation, imports, and industrial facilities producing more than 25 thousand tons of carbon dioxide (CO2) equivalents. In 2015, the policy was extended to distributors of petroleum and natural gas.

In California, regulated facilities must comply with the policy by surrendering permits according to the amounts of emissions produced. While a fraction of the emission permits are allocated for free, the remaining are auctioned quarterly and traded in a permits market. The allocation of free permits at the plant level is undisclosed. However, according to the California Air Resources Board, the free allocation of permits between 2013 and 2017 targeted, on average, around 85% of the emissions produced by a theoretical industrial facility subject to the policy.[5] The surrendering of emission permits occurs *ex-post*, relative to the emissions produced over the past years. Therefore, the effects of the program are expected to be significantly observable only from the first year after its introduction or amendments. The average supplier subject to the policy produced 2605 thousand tons of CO2 equivalents in its California facilities subject to the cap-and-trade in 2013. The auction price of permits was $10 per metric ton of CO2 equivalents in 2013, and it averaged approximately $12.50 over the period between 2013 and 2017.

3 Data and methodology

3.1 Data sources and sample construction

To assess the effects of environmental policy shocks on the supply chain, we combine data from three sources: supply chain relationships and firm competitors from FactSet Revere, facility-level carbon emissions from the U.S. Environmental Protection Agency (EPA), and firm-level financial data from Compustat.

We obtain supply chain relationships and competitor data from FactSet Revere. This dataset covers mostly publicly listed companies involved in global corporate relationships since 2003. Data on supply-chain relationships and direct business competitors is collected

[5]For these calculations, the California Air Resources Board assumes constant output and emission efficiency (refer to https://ww2.arb.ca.gov/our-work/programs/cap-and-trade-program/allowance-allocation).

by relying on sources such as SEC 10-K annual filings, investor presentations, and press releases.

We gather information on firms' facility-level emissions from the U.S. Environmental Protection Agency (EPA). Since October 2009, the EPA has published the Greenhouse Gas Reporting Program (GHGRP). The GHGRP provides information on the universe of U.S. establishments that emit 25 thousand tons or more of CO2 equivalents per year. These data are publicly available through the Program's Facility Level Information on GHGs Tool (FLIGHT). We manually merge facility-level emissions data to firm-level information from FactSet using the parent names disclosed by the EPA. When parent names are unmatched, we rely on the facility names for the merge.

Finally, we gather financial data, as well as information on the industry of customers and suppliers, from the Compustat North America and Global Fundamentals database. We merge Compustat to FactSet data using PERMCO identifiers obtained through CRSP.

Our baseline unmatched sample consists of a panel of approximately 356,000 FactSet supplier-customer pair-year observations with financial information about the supplier over the period 2010–2017. This sample period allows us to study the evolution of supply chains from the onset of EPA emissions reporting, three years before the introduction of the California cap-and-trade in 2013, until four years after the introduction of the program. The sample comprises 4,735 unique suppliers and 34,052 unique business customers. 61 of the suppliers have at least one facility in California that is subject to the cap-and-trade program ("treated suppliers"). Treated suppliers have 2,365 unique customers. The remaining 4,674 suppliers are not treated. From FactSet Revere, we can also identify the direct competitors of the treated suppliers. Figure 1 provides an example of our dataset's structure for the case of a treated firm, U.S. Steel, which owns a facility close to San Francisco producing enough emissions to be subject to the cap-and-trade. This firm, as well as its direct competitors (namely Steel Dynamics, NUCOR, and AK Steel), is a supplier of Worthington

Industries. In some of our analyses, we compare the evolution over time of supplier-customer pairs involving a treated supplier (such as the pair U.S. Steel-Worthington Industries) to a supplier-customer pair containing a competitor of the treated firm selling to a common customer (e.g., NUCOR-Worthington Industries).

To analyze the environmental consequences of the cap-and-trade, we augment the data set by including firm-level CO2 emissions from ICE Climate Transition Finance (previously known as Urgentem). We merge these data using the ISIN codes of suppliers and customers. These data include emissions directly reported by the firms (sourced from CDP) and inferred emissions produced by the ICE Climate Transition Finance team.[6] 494 of our sample suppliers report their scope 1 or 2 emissions to the CDP between 2010 and 2017. Over the same period, only 212 customers reported their upstream scope 3 emissions (i.e., "goods and services" linked scope 3 emissions) to the CDP, while ICE estimates upstream scope 3 emissions for 542 suppliers.

Table 1 provides some summary statistics for the baseline sample. Table A2 in the Appendix defines the variables. Panel A shows that each year, about one out of five supplier-customer relationships are terminated (i.e., the average probability of observing the termination of an existing relationship of 21%). The probability of observing the beginning of a new relationship is 32% on average. The maximum length of supplier-customer relationships in our sample is 15 years, and the average length is slightly higher than three years. This suggests that the time window in our estimations – three years before the introduction of the California cap-and-trade and up to four years after – is sufficient to capture the dynamic component of the effect and its persistence while excluding possible confounding effects. A comparison of Panels A, B, and C indicates that larger suppliers and customers are relatively more represented in the FactSet sample than smaller ones due to their presence within several production networks. In addition, customers are larger than their suppliers, and suppliers

[6] Dunz, Emambakhsh, Hennig, Kaijser, Kouratzoglou, and Salleo (2021) provide a detailed description of the inference approach adopted by the data provider.

have more than 13 customers on average.

3.2 Empirical strategy

Our main empirical strategy tests whether the introduction of the California cap-and-trade program has led to a rewiring of the supply chain outside the boundaries of the jurisdiction. Specifically, we test whether suppliers affected by the program are more likely to experience the termination of their customer relationships.

To identify whether differences in customer relationships arise from the cap-and-trade program, our empirical methodology exploits cap-and-trade program-affected suppliers and the timing of the policy. We perform difference-in-differences estimations by comparing changes in the probability of termination between treatment and control groups around the program enactment in 2013 (the treatment). Specifically, we estimate the regression:

$$Ending_{s,c,t+1} = \beta Treated_s \times Post_t + \gamma_1' X_{s,t} + \gamma_2 z_{s,c,t} + \mu_s + \eta_{c,t} + \epsilon_{s,c,t}. \quad (1)$$

The dependent variable, $Ending_{s,c,t+1}$, is a dummy variable that takes the value one if the supplier-customer relationship ends in a given year (i.e., it is not observed in FactSet in year $t+1$), and zero if the relationship is observed in t and continues into $t+1$. We account for M&As, delistings, or bankruptcies of one of the parties by eliminating suppliers or customers in pairs that end their relationship on the same year that one of the two firms exits the Compustat sample. $Treated_s$ is a dummy variable that takes the value of one for suppliers s that have at least one facility in California reporting emissions above 25 thousand tons of CO2 equivalents at the onset of the EPA emission disclosure policy (2010). $Post_t$ is a dummy variable that takes the value of one in 2013 and thereafter and zero otherwise.

$X_{s,t}$ includes suppliers' size (log of total assets), profitability (EBITDA over total assets), leverage (short and long-term debt over assets), Tobin's Q, and R&D investment (R&D stock over assets). $z_{s,c,t}$ includes the length of the relationship between suppliers and customers computed on the entire FactSet sample (i.e., accounting for the length of the relationships between time t and the first time the supplier-customer link is observed in FactSet, even before the beginning of the sample period). These controls might be correlated with the treatment if firms with business activity in California present specific features that can be measured along those dimensions (e.g., they are characterized by higher profitability in given years), and with the outcome variable of interest (e.g., it might be less convenient to exit a business relationship with a highly profitable firm). We saturate the specification with supplier-fixed effects, supplier sector-by-year-fixed effects, and customer-by-year fixed effects. Robust standard errors are clustered at the supplier level.

We mitigate reverse causality concerns by fixing our treated dummy variable in 2010, i.e., three years before the start of the California cap-and-trade program. To the extent that firms' pre-program supply chain structure is their first best choice, on average, firms would not have incentives to alter their optimal supply chain composition ahead of the introduction of the program. Setting the treatment several years ahead of the introduction of the program is a conservative approach: if some firms in the treatment group reduce emissions below the regulatory threshold between 2010 and 2012 and become unaffected by the program, then any negative effect of the program would be weakened, leading to an attenuation of the effect captured by our estimates. Our estimates would be similarly attenuated if firms in the control group increase their emissions above the program threshold before the program's introduction.

Our main coefficient of interest is the estimate of β. Given the customer-by-year fixed effects, this coefficient captures the variation in the change in the probability of termination between suppliers affected by the program (treated) relative to suppliers not subject to the program (control) selling to the same customer. For this reason, our results are unlikely to be driven by changes in firm-specific demand. The estimated difference in the probability of termination can, therefore, be plausibly attributed to supply-side factors. To the extent that the program places affected suppliers at a disadvantage relative to competitors, we expect β to be positive. Our identification strategy assumes that the probability of ending the relationship with a treated and control supplier would have been the same in the absence of the policy (parallel trends). We discuss this assumption in Section 4.

Table 2 shows that treatment and control groups differ significantly across several observable characteristics. To address this issue, we estimate Equation (1) on a matched sample using several alternative matching approaches. In our baseline approach, we select suppliers headquartered in the United States, we match them exactly based on their industry (based on SIC two-digit codes), and we use a propensity score weighting approach for firms' pre-treatment size and profitability. We match each treated supplier with replacement to a minimum of three control suppliers using the nearest neighbor algorithm. Figure 2 shows that the standardized difference in means along the dimensions of size and profitability is closer to zero after the match. Table 3 contains summary statistics for our baseline matched sample. The table shows that the customer-supplier pairs in our matched sample have similar characteristics as in the wider baseline sample reported in Table 1.

In an alternative matching approach, we compare treated firms to their direct competitors, as reported in FactSet. Specifically, for each treated supplier, we select its direct competitors reported in FactSet over the sample period and we keep the competitor groups fixed in the analysis. This approach is consistent with competitor groups being stable or slow-moving over time and it allows us to partially circumvent cases in which firms strategically decide to report a competitor or not. Within the group of competitors, we select the controls based on propensity score weighting on pre-treatment size and profitability. With this approach, we mitigate the concern that the 2-digit SIC codes do not capture well the market within which a firm operates. For specifications that rely on this alternative matching strategy, we substitute the baseline fixed effects at the supplier and customer-by-year level (μ_s and $\eta_{c,t}$ respectively) with supplier-by-competitor group and customer-by-year-by-competitor group fixed effects

($\mu_{g(s)}$ and $\eta_{g(s),c,t}$ respectively, where $g(s)$ identifies the group of direct competitors of each treated firm s). This allows us to study the effect of interest within the group of competitors of each treated supplier. In other words, we compare the probability that a customer terminates its business relationship with a treated supplier after the introduction of the cap-and-trade program relative to the probability of terminating its business relationship with a direct competitor (not subject to the program) of the treated supplier.

4 Results

In this section, we present the results of the baseline difference-in-differences regression testing the rewiring of supply chains away from the California cap-and-trade program. We then discuss the identifying assumption and conduct robustness checks for our baseline results. We conclude by testing for alternative interpretations of our baseline results.

4.1 Rewiring supply chains in avoidance of the cap-and-trade

Table 4 presents the results of estimating Equation (1) on our baseline matched sample with different sets of control variables. The estimates in column (1) only control for supplier fixed effects and supplier sector-by-year fixed effects. The coefficient of the interaction $Treated \times Post$ is positive but not statistically significant. Indeed, this specification explains a limited portion of the variation in the data as it does not control for any demand-side effect, hence possibly biasing the estimates. The R^2 of the regression increases from 0.171 to 0.830 when we include customer-by-year fixed effects from column (2) onwards. In these regressions, we keep the sample fixed to isolate the impact of introducing fixed effects that absorb any bias arising from unobservable customer-level shocks. In turn, these specifications compare treated suppliers with control suppliers selling to the same customer in a given year.

In column (2), the estimate of the interaction $Treated \times Post$ is statistically significant. In columns (3)-(5), we include supplier and pair controls. The coefficient in column (3) suggests that the California cap-and-trade program leads to a 5.3 percentage point higher likelihood that a given customer ends the relationship with its California-affected supplier relative to another supplier not subject to the program. This coefficient is statistically significant and economically significant, representing a 25% (= 0.053/0.209) increase relative to the average unconditional probability of terminating the relationship with a supplier.

In column (4), we estimate our baseline specification on a matched sample that excludes customers with California facilities producing emissions above 25 thousand tons of CO2 equivalents (i.e., treated customers). While we control for the effect of any shock at the customer-year level using fixed effects, this exclusion further mitigates the concern that the effect observed is driven by treated customers rather than by treated suppliers. The economic size of the estimate is in line with that observed in column (3), which confirms that customer-by-year fixed effects control for most of the customer-driven effect and suggests that the exclusion restriction holds in our preferred baseline specification in column (3). Finally, in column (5), we match each treated supplier with its group of direct competitors, and we compare treated suppliers with their direct competitors outside of California, which share a customer in a given year. The effect of interest remains statistically significant. It is also economically meaningful, representing an increase of 12% relative to the average unconditional probability of ending a relationship with a supplier.

4.2 Identifying assumption

In this section, we perform tests for the validity of the identifying assumption underlying our empirical setting. Figure 3 shows the dynamic difference-in-differences effect following the California cap-and-trade event. The figure shows that treated suppliers experience an increase in the probability of experiencing the termination of their pre-existing customer relationships only after the introduction of the cap-and-trade. The coefficients of the interaction term are not statistically distinguishable from zero for the years before the policy was introduced.

Thus, there is no evidence of pre-existing differential trends between treated and control firms.

Figure 3 also shows the dynamics of the effect. The coefficient is statistically significant in the years following the introduction and amendment of the regulation, in 2013 and 2015, respectively. This is consistent with the costs of the policy being reflected on treated suppliers' performance only after the first year of its introduction or amendments. Indeed, the California cap-and-trade program requires suppliers to purchase allowances yearly to meet part of their previous year's emissions. The rewiring of the supply chain is likely to follow. In 2017, after the termination of several treated supplier-customer relationships in 2014 and 2016, fewer outstanding treated supplier-customer relationships are left, and therefore, the rewiring is less prevalent.

4.3 Robustness and extensions

So far, our results suggest that with the introduction of the California cap-and-trade program, treated suppliers face an increase in the probability of experiencing the termination of customer relationships vis-a-vis control suppliers. In this section, we test for the robustness of our baseline results on alternative samples and using alternative specifications.

Generalized difference-in-differences. We start by testing whether the effect observed in our baseline results intensifies for suppliers that produce relatively more emissions in California. Suppliers' emissions in California define the intensity of their treatment because the costs for affected firms grow with their emissions in California. Therefore, we test the robustness of our baseline estimation to the use of a continuous treatment variable corresponding to firms' California emissions (above 25 thousand tons of CO2 equivalents). To test this, we estimate Equation 1 substituting the binary variable $Treated_s$ with a continuous treatment variable $Intensity\ of\ Treatment_s$. We compute this measure as the ratio of the firm's total

California emissions above 25 thousand tons of CO2 equivalents in 2010, normalized by the firm's total assets. For ease of interpretation of the estimates, we standardize this measure by dividing it by its standard deviation. We set the value equal to zero for suppliers in the control group. Consistent with our baseline results, Table 5 reports positive and statistically significant coefficients of interest on the interaction term, suggesting that the probability of terminating a relationship with a treated supplier increases as its emissions increase in California.

Alternative standard error clustering. In our baseline specification, we cluster standard errors at the supplier level. This controls for the correlation of the standard errors for a given supplier over time. The choice is motivated by the treatment being allocated at the supplier level at the beginning of the sample period. However, we also conduct robustness tests using standard errors clustered at the pair level (in line with literature adopting a similar empirical strategy, such as Pankratz and Schiller, 2023). Column (1) in Table 6 shows that our results are robust to alternative clustering choices, using the same specification as in column (3) of Table 4.

Alternative treatment dummy variable. In Table 6, column (2), we show the baseline results for an alternative allocation of suppliers into treatment and control groups. Treated suppliers have facilities in California with emissions above 25 thousand tons of CO2 equivalents in 2012 (one year before the event) rather than in 2010 as in our baseline case. These treated suppliers are matched to control suppliers using the same exact matching and propensity score weighting approach used in the baseline estimation. 80% of the treated observations according to the baseline definition of the treatment are also treated in this alternative approach. Selecting treated suppliers in the year prior to the event raises concerns of biases in the estimation due to potential anticipating effects. However, baseline results are robust to this alternative specification.

Suppliers geographically concentrated in California. In Table 6, column (3), we report the estimates of the baseline specification after excluding from the sample treated suppliers that are geographically diversified. To select these suppliers, we replicate the firm-level geographical diversification measure estimated by Bartram et al. (2022). Suppliers that are not geographically diversified do not have the opportunity to easily reduce their exposure to the cap-and-trade by shifting their production to facilities outside of California. The table shows that non-geographically diversified suppliers experience a 5.5 percentage point higher increase in the probability of termination of customer relationships relative to control suppliers. Therefore, our results are not exclusively driven by within-firm reallocation of production to facilities outside of California.

Financially constrained suppliers. In Table 6, column (4), we report the estimates of the baseline specification for a sub-sample in which treated suppliers are exclusively those that are not financially constrained. To select these suppliers, we replicate the approach proposed by Bartram et al. (2022), and we indicate firms that appear as financially constrained in at least four of six measures of financial constraints (firms' size, their dividend payouts, their short and long-term debt rating, their Kaplan and Zingales, 1997 index, their Whited and Wu, 2006 index and their Hadlock and Pierce, 2010 index) computed strictly before the beginning of the sample period (between 2003 and 2008). This allows us to select treated suppliers that do not significantly relocate their economic activity to their facilities located outside California, as per previous evidence of carbon leakage (Bartram et al., 2022). Similarly to the previous robustness test, if within-firm carbon leakage were to be the only driver of our results, we would not find a significant result on the sub-sample of treated suppliers that are not financially constrained. The table shows that the baseline results also hold on this sub-sample.

Conditional logit. In Table 6, column (5), we report the estimates of the baseline specification using a conditional logit estimator. This approach addresses the concern that probabilities could be assigned values outside the 0-1 interval when using a linear probability estimator. The coefficients are estimated on the same matched sample that underlies our baseline specification (column (2), Table 4). We use customer-by-year fixed effects and supplier-sector fixed effects. Due to computational constraints, we leave out supplier fixed effects, and while we estimate the regression on our matched baseline sample, we do not weight the observations according to our propensity score weighting approach. The results are aligned with the baseline results. The estimate of the coefficient of interest is positive and statistically significant.

Placebo test. Table 6, column (6), shows the baseline results for an alternative treatment group. Suppliers belong to the placebo treatment group if they are headquartered in California, albeit not having facilities in California with emissions above 25 thousand tons of CO2 equivalents in 2010. Non-treated suppliers that are part of the placebo group – i.e., with headquarters in California – are mostly "tech firms". Examples in our sample are HP Inc. and DSP Group. Suppliers with placebo treatment are matched to non-treated suppliers using the same propensity score weighting approach used in the baseline estimation. Suppliers with placebo treatment do not face a significant increase in their probability of experiencing the termination of pre-existing relationships with customers after the introduction of the cap-and-trade program. Indeed, while these suppliers are headquartered in California, thus experiencing the cap-and-trade-induced increase in electricity prices in their headquarters' offices, they do not directly bear all of the costs of the new environmental policy. Therefore, their customers may not have the incentive to rewire their supply chain away from these placebo suppliers.

Spillover test. Table 6, column (7), shows the results for an alternative treatment group that allows for testing whether the effect of the introduction of the California cap-and-trade spills over to suppliers that pollute in different states (suppliers in the control group). In this case, the most affected suppliers, excluding the ones directly affected by the cap-and-trade, would be those producing more than 25 thousand tons of CO2 equivalents in states that are relatively more likely to introduce a cap-and-trade following California. These states might be the ones that joined the U.S. Climate Alliance with California at its onset in 2017.[7] Suppliers in the baseline matched control group and that produce significant emissions in these states (i.e., emissions above 25 thousand tons of CO2 equivalents based on their 2010 EPA reporting) are matched to other control suppliers adopting the same propensity score weighting approach used in the baseline estimation. Overall, suppliers emitting in (2017) U.S. Climate Alliance states do not experience a significant increase in their probability of experiencing the termination of pre-existing customer relationships. This indicates that customers do not significantly rewire their supply chain preemptively on average and that the cap-and-trade shock does not significantly spill over to the control group.

Shifting the customer base. In our baseline results, we document that suppliers subject to the California cap-and-trade are more likely to experience the termination of their customer relationships. We interpret this evidence as being suggestive of the rewiring of supply chains away from the cap-and-trade. However, if different customers started new relationships with affected suppliers, our baseline results would suggest a shift in treated suppliers' customer base rather than providing evidence of the rewiring of supply chains outside the California

[7]We thank von Meyerinck, Niessen-Ruenzi, Schmid, and Davidoff Solomon (2021) for sharing with us the data and for suggesting an empirical approach. The states in the U.S. Climate Alliance in 2017, apart from California, are Colorado, Connecticut, Delaware, Hawaii, Massachusetts, Minnesota, New York, North Carolina, Oregon, Rhode Island, Vermont, Virginia, and Washington.

cap-and-trade.

To address this possible alternative interpretation of our results, we investigate the probability of beginning new relationships with treated suppliers using a difference-in-differences approach similar to the baseline regression. Specifically, we estimate the following linear probability model:

$$Beginning_{s,c,t} = \beta Treated_s \times Post_t + \gamma_1' X_{s,t} + \mu_s + \eta_{c,t} + \epsilon_{s,c,t}, \tag{2}$$

where $Beginning_{s,c,t}$ is a dummy variable that takes the value of one if the relationship between a given supplier s and its customer c is observed in year t, but not in year $t-1$. To select these cases, we reintroduce in the sample the supplier-customer relationships observed in FactSet one year before the beginning of the sample period (i.e., we add 2009 relationships to the data set), and we drop them after the construction of the dummy variable. We rely on the same matching approach adopted in the baseline estimation.

Table 7 shows that suppliers affected by the introduction of the California cap-and-trade are less likely to begin new relationships with customers. Results are consistent throughout specifications with supplier and customer-by-year fixed effects (with and without time-varying controls at the supplier level), supplier-by-competitor group and customer-by-year-by-competitor group fixed effects, and a specification that excludes treated customers from the sample. Overall, these findings confirm the interpretation of our baseline results as a rewiring of supply chains outside the jurisdiction of the California cap-and-trade program.

Alternative matching approaches. In Table A3 of the Internet Appendix, we report results of the baseline specification described in Equation (1) estimated over an unmatched sample in column (1), and samples constructed using several alternative matching approaches, from column (2) to (5). Specifically, in column (2), we repeat the propensity score weighting approach adopted in the baseline estimation, but we augment the set of matching controls, including suppliers' pre-treatment debt. In column (3), we further augment this set to account for the role of cash reserves to protect against risks arising from supply chain relationships (Kulchania and Thomas, 2017). Thus, we also include suppliers' pre-treatment Tobin's Q, R&D stock, and cash. In column (4), we filter for suppliers headquartered in the United States, and we adopt an exact match based on suppliers' sector and customer-by-year and a propensity score match based on suppliers' pre-treatment size and profitability. Using the nearest neighbor algorithm, we select at least one control for each treated supplier. In column (5), we repeat the previous approach, but we weight the observations based on propensity score. The estimates for the coefficient on the main variable of interest remain positive and statistically significant. This suggests that our matching approach does not drive our results. Moreover, the R^2 of the regressions relying on alternative matching approaches is always lower than, or at most equal to the R^2 in our baseline regression, supporting the choice of the baseline approach as our preferred one.

5 Economic mechanisms

So far we have established a link between the introduction of the California cap-and-trade program and the rewiring of supply chain networks away from suppliers subject to the heightened climate transition risks the policy produces. In this section, we investigate possible economic mechanisms that drive the rewiring of supply chains outside the cap-and-trade program.

5.1 Competitiveness channel

One prediction of the competitiveness channel of carbon leakage is that customers can more easily shift their supply chains away from suppliers exposed to climate transition risks if these operate in more competitive industries. In these cases, customers can avoid possible supply chain risks arising from the cap-and-trade by selecting among a large number of substitutable suppliers.

Therefore, we first assess the competitiveness channel of carbon leakage by reproducing our baseline regression in sub-samples characterized by different levels of product market competition. In Table 8, we report our estimates for the baseline coefficients estimated on a sub-sample characterized by an average pre-treatment HHI concentration index above or below the pre-treatment sample median. We compute the HHI at the three-digit SIC code level in columns (1) and (2), or within the matched competitors' group of each treated supplier in columns (5) and (6). In addition, we study the effect over a sub-sample of suppliers with a Lerner Index (computed as the average ratio of net income over sales, capped between zero and one) above or below the median in columns (3) and (4). Columns (7) and (8) present estimates for suppliers exposed to an average pre-treatment number of competitors in their matched competitors' group below or above the pre-treatment median. We find that results are significant and economically sizeable for suppliers operating in more competitive industries across all measures of product market competition. Thus, the effect is significant in less concentrated industries (low HHI), industries with lower Lernex index, and industries with more competitors.

Another prediction of the competitiveness channel of carbon leakage is that switching costs may play a role in the rewiring of supply chains outside the cap-and-trade program. Indeed, industries characterized by low input specificity, and thus easier to substitute, should experience a higher likelihood of termination of their business relationships when exposed to heightened transition risks (Barrot and Sauvagnat, 2016). Similarly, this effect should be especially concentrated among customer-supplier pairs characterized by weaker ties, as customers might be less locked in the relationship with their suppliers.

Therefore, we assess the competitiveness channel of carbon leakage by splitting the sample into relationships with high and low switching costs and estimating equation (1) in the resulting sub-samples. In Panel A of Table 9, we split the sample according to supplier characteristics: specialized versus standardized goods according to the two-digit SIC code classification proposed by Giannetti, Burkart, and Ellingsen, 2011; and high versus low R&D

stock). In Panel B, we split the sample according to the strength of the ties between the customer and the supplier.

In line with the outlined economic mechanism, Panel A of Table 9 shows that the increase in treated suppliers' probability of experiencing the termination of customer relationships is concentrated among suppliers producing standardized inputs and suppliers with below-median R&D stock over assets ratio. Indeed, forming and maintaining customized supplier-customer relationships is costly, implying that firms face nontrivial decisions to build or terminate relationships with their suppliers and customers. The results in Panel B show that the effect of the cap-and-trade program is more pronounced when switching costs are lower as proxied by the geographic proximity of customers and suppliers (columns (1) and (2)), and the length of the relationships with their customers (columns (3) and (4)).

Next, we sharpen our analysis of economic mechanisms underlying our results by studying affected suppliers' financial performance. In line with anecdotal evidence from affected suppliers' SEC filings reported in Table A1, the introduction of the California cap-and-trade places affected suppliers at a disadvantage compared to competitors. Thus, we expect to observe a decline in their financial performance.

To test this hypothesis, we collapse our pair-year panel into a supplier-year panel and estimate the following regression model:

$$Y_{s,t+1} = \beta_1 Specialized_s \times Treated_s \times Post_t + \beta_2 Treated_s \times Post_t + \eta_s + \mu_{I(s),t} + \epsilon_{s,t}. \quad (3)$$

$Y_{s,t+1}$ is the supplier's average costs (COGS over total assets), output (log revenues), size (log of total assets), change in tangible assets (change in PPE over total assets) or profitability (net income or EBITDA over total assets). $Specialized_s$ is a dummy variable that takes the value of one for suppliers producing specialized inputs (Giannetti et al., 2011). We saturate the specification using supplier (η_s) and industry-by-year ($\mu_{I(s),t}$) fixed effects. Table 10 reports the results. Mirroring the approach adopted in the baseline specification, we select suppliers headquartered in the United States and we match treated to non-treated suppliers using an exact match on two-digit SIC codes and a propensity score weighting approach based on size and profitability. We rely on the nearest neighbor algorithm that matches at least one control supplier to each treated supplier. For each supplier, the maximum weight assigned by the algorithm in the pre-treatment period is extended to all the observations of the supplier over the sample.

Columns (1) and (2) of Table 10, Panel A, show that the affected suppliers' average costs are relatively higher after the introduction of the California cap-and-trade. The effect is larger, albeit not significantly, among suppliers producing standardized inputs. Although our measure does not provide insights into suppliers' marginal costs, an increase in normalized COGS is consistent with an increase in cost induced by the cap-and-trade (e.g., the cost of emission permits, the monitoring and reporting of greenhouse gases produced and the increase in other raw input prices). Columns (3), (4), (5) and (6) show that treated suppliers shrink in size after the introduction of the policy, with the effect being driven by the producers of standardized inputs, who also experience a decrease in their tangible assets.

The results in Panel B show that affected suppliers experience a drop in their profitability, which is consistent with the competitiveness channel of carbon leakage. The effect is especially driven by suppliers producing standardized inputs. These results confirm that the California cap-and-trade program is a negative shock for affected suppliers. This impact is most pronounced when the costs for their customers to switch to outside options are relatively low. Instead, suppliers producing specialized inputs are likely able to pass part of the cap-and-trade costs to their customers, which explains the results.

We conclude our exploration of the competitiveness channel of carbon leakage by testing whether the transition risk shock propagates through the production network to customers indirectly exposed to the program. If customers can timely and efficiently break their ties with suppliers subject to the program, they should be isolated from the shock's propagation.

Moreover, we do not expect customers to suffer significant financial losses due to switching to a different supplier after the introduction of the program because we observe that the termination of relationships is mostly prevalent when switching costs are relatively low.

We collapse the pair-year panel on a customer-year panel, excluding customers directly affected by the cap-and-trade, and estimate the following regression model:

$$Y_{c,t+1} = \beta HasTreatedSupplier_c \times Post_t + \eta_c + \mu_{I(s),t} + \epsilon_{c,t}. \quad (4)$$

$Y_{c,t+1}$ is the customer's average costs (COGS over total assets), output (log revenues), size (log of total assets), change in tangible assets (change in PPE over total assets) or profitability (net income or EBITDA over total assets). $HasTreatedSupplier_c$ is a dummy variable that takes the value of one if the customer has at least one treated supplier after the event, and zero otherwise. As before, we match indirectly treated to non-indirectly-treated customers using an exact match on two-digit SIC codes and a propensity score weighting as in our baseline approach. We saturate the specification using customer and industry-by-year fixed effects.

Table 11 reports the results. We find that customers exposed to treated suppliers do not experience a significant worsening of their profitability and that the cap-and-trade shock does not significantly propagate to their costs, output, size, and profitability.

5.2 Customers' climate transition risks

We have provided evidence consistent with the competitiveness channel of carbon leakage driving the rewire of supply chains away from suppliers subject to the California cap-and-trade. In this section, we analyze whether customers' climate transition risk awareness or the anticipation of future environmental policy outside of California might mitigate the observed effects.

Customers with relatively higher exposure to climate transition risks might be less likely to rewire their supply chain away from the California cap-and-trade. Indeed, despite being at risk of supply chain disruptions due to suppliers' exposure to climate transition risks, customers that anticipate future regulation of their supply chain emissions or experience higher environmental awareness might prefer to retain relationships with suppliers subject to the cap-and-trade to benefit from a potential reduction in their scope 3 emissions. We test this hypothesis by conducting our analysis over the sub-sample of customers split at the pre-treatment industry level median in terms of the proxy for attention to climate change provided by Sautner et al. (2023).[8] In Table 12, we show that the rewiring is concentrated among customers with weaker environmental awareness. We proceed by using alternative firm-level proxies of climate transition risk exposure. In columns (3)-(6), we study the effect in sub-samples of customers headquartered in Democrat or Republican states as per their 2016 elections or in states that are members of the (2017) U.S. Climate Alliance coalition.

We use these measures as a non-time-varying proxy for the sensitivity to environmental issues in these states and, thus, of a higher climate transition risk. Overall, these results confirm that the rewiring is especially concentrated among customers headquartered in states with relatively lower climate transition risks.

6 Environmental implications

In this section, we examine the environmental implications of the supply chain-driven carbon leakage due to the California cap-and-trade program.

For this analysis, we construct firm- and supply chain-level emissions measures. We begin by collecting each supplier's U.S.-wide facility-level emissions from the EPA database, sum them up at the supplier level, and generate a measure of their emission intensity (i.e., emissions normalized by a firm's assets). We obtain the U.S.-wide EPA emissions of 437

[8] This measure is based on the presence of climate change-related words in analysts and management talk during earnings calls. It is defined at the firm level, and it is time-varying with yearly frequency. Data is available at: Sautner, Van Lent, Vilkov, and Zhang (2020).

suppliers in FactSet between 2010 and 2017. Next, we exploit our supply chain linkages data and, as a proxy for supply chain emissions, we compute the total U.S.-wide direct supply chain emissions and the average U.S.-wide direct supply chain emission intensity of each customer in each year.

Our self-constructed measures have some disadvantages relative to emissions data from commercial data providers. The main disadvantage is that they only partially account for the emissions produced by the firms. This is because we collect the data from a U.S.-wide EPA disclosure standard that applies as a mandatory requirement only for facilities that produce at least 25 thousand tons of CO2 equivalents in the U.S. This possibly leaves out several smaller and non-U.S. facilities. On the other hand, our measures overcome the known quality issues that characterize inferred scope 3 emissions data (Aswani et al., 2024), which researchers often need to resort to due to the scarce reporting of corporate scope 3 emissions. Importantly, our proxy of supply chain emissions differs from customers' scope 3 emissions. Our estimate measures the entire footprint of each customer's first-level supplier. Instead, upstream scope 3 emissions inferred by data providers account for the emissions produced along each customer's entire supply chain and scale the footprint of suppliers by the amounts of goods and services a customer purchases from the given supplier.

With these caveats in mind, we use these data to study the environmental effects of the California cap-and-trade on affected firms' emissions and on the supply chain emissions of customers of affected firms. Panel A of Table 13 focuses on the direct emissions of treated firms. Specifically, it shows the estimates of the coefficients in Equation (3), where $Y_{s,t+1}$ stands for several measures of firm emissions. In columns (1) and (2), these measures are, respectively, a supplier's U.S.-wide emissions (computed with the procedure described above) and the U.S.-wide emission intensity from EPA. In columns (3) and (4), we use total scope 1 and 2 emissions from ICE Climate Transition Finance and the total scope 1 and 2 emission intensity. Our evidence does not suggest that treated suppliers experience a reduction in their direct emissions after the introduction of the cap-and-trade. Rather, they report higher U.S.-wide emissions and emission intensity.

Next, in Panel B, we study the supply chain emissions of customers indirectly exposed to the policy through their suppliers. We test the specification described in Equation (4). In columns (1) and (2), $Y_{c,t+1}$ is equal to the sum of the U.S.-wide emissions of each customer's direct suppliers and the average of their U.S.-wide emission intensity as a proxy for supply chain emissions. In columns (3) and (4), we use ICE scope 3 emissions associated with goods and services. Due to data availability limitations inherent in the horizon of our sample, we use inferred scope 3 emissions data. We find that customers exposed to treated suppliers experience a significant worsening of their supply chain environmental performance. These results suggest that the California cap-and-trade policy could have unintentionally resulted in a shift of economic activity toward more polluting supply chains. Customers indirectly affected by the policy – which rewired their supply chains away from California, as per our baseline results – switched to more polluting suppliers outside the carbon pricing regime, where the cost of producing emissions or relying on polluting fuels in the production activity is relatively lower.

7 Conclusions

Over the past decades, several countries have introduced environmental policies to regulate firms' carbon emissions. However, many of these initiatives have not been coordinated across regions and countries. In this paper, we provide evidence of a new channel of carbon pricing policies – the product market competition channel— which leads to a rewiring of supply chains, thereby contributing to the carbon leakage phenomenon.

Using a difference-in-differences approach combined with a matching approach, we find that suppliers subject to the California cap-and-trade policy are more likely to experience the termination of pre-existing customer relationships. The economic magnitude of the effect ranges from a 2.5 to a 6.1 percentage point increase in the probability of terminating these relationships. Moreover, suppliers exposed to the policy are less likely to begin new customer relationships after the event. Overall, these findings are consistent with the rewiring of supply chain networks outside the cap-and-trade program.

Our results are consistent with the competitiveness channel of carbon pricing policies. Importantly, the effect is concentrated among suppliers operating in less concentrated markets, those producing standardized inputs or with low R&D, and those with weaker ties with their customers. Consistent with being at a disadvantage relative to competitors after the introduction of the cap-and-trade program, suppliers suffer a deterioration in their financial performance, especially if they produce standardized inputs. Moreover, the results are concentrated among customers headquartered in states with a relatively weaker environmental awareness, where future carbon pricing is relatively less likely.

We also explore the environmental implications of carbon pricing policies. We find that, after the introduction of the cap-and-trade program, affected suppliers do not report improved direct emissions. Furthermore, we find a worse supply chain carbon footprint of customers affected through the supply chain. Taken together, our findings provide new insights into the side effects of carbon pricing policies that can, at least partially, offset the positive effects of these policies.

Our paper has important policy implications and adds to the discussion on the need for coordinated climate action. Our findings suggest that coordinating climate policy across jurisdictions and regulating Scope 3 emissions would improve the market conditions for firms competing across regions or countries with heterogeneous climate policies. In fact, regulating the emissions produced along the supply chain emerges as an adequate approach to address the competitiveness channel of carbon leakage as an alternative to a carbon border adjustment mechanism.

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Table 1: Summary Statistics on Unmatched Sample

	Mean	Std. Dev.	Median	Min	Max	Obs.
Panel A: Pair-Year Data						
Ending	0.21	0.41	0.00	0.00	1.00	355,999
Starting	0.32	0.47	0.00	0.00	1.00	355,999
Relationship length (years)	3.15	2.60	2.00	1.00	15.00	355,999
Number of customers	45.67	57.59	29.00	1.00	534.00	355,999
Number of suppliers	33.12	85.08	9.00	1.00	690.00	355,999
Supplier treated (2010)	0.03	0.17	0.00	0.00	1.00	355,999
Supplier CA emission intensity std.	0.06	1.00	0.00	0.00	27.75	355,999
Supplier total assets (billion USD)	29.24	77.90	2.58	0.01	531.86	355,405
Supplier profitability	0.07	0.16	0.10	-0.80	0.34	339,609
Supplier debt	0.25	0.21	0.22	0.00	0.99	353,557
Supplier Tobin Q	1.97	1.37	1.54	0.61	8.81	321,736
Supplier R&D stock	0.39	0.75	0.10	0.00	5.51	355,999
Customer total assets (billion USD)	68.22	145.55	14.33	0.02	1027.62	128,681
Panel B: Supplier-Year Data						
Supplier treated (2010)	0.01	0.12	0.00	0.00	1.00	32,976
Total assets (billion USD)	12.59	44.22	0.93	0.00	348.13	32,555
Revenues (billion USD)	5.17	14.17	0.59	0.00	96.41	32,505
Net income/Assets	-0.09	0.45	0.02	-3.16	0.48	26,266
EBITDA/Assets	0.01	0.38	0.09	-2.33	0.52	27,794
COGS/Assets	0.61	0.68	0.41	0.00	3.81	27,841
ΔPPE/Assets	0.02	0.11	0.00	-0.23	0.66	27,658
Number of customers	13.41	21.01	6.00	1.00	534.00	25,504
U.S.-wide emissions	4934.65	12946.09	412.93	0.00	86308.60	2,694
U.S.-wide emission intensity	416.33	877.79	78.73	0.00	5688.41	2,689
Scope 1-2 emissions	6055.46	16541.03	661.96	7.50	116367.88	2,965
Scope 1-2 emission intensity	320.14	904.73	35.22	0.63	5945.01	2,967
Panel C: Customer-Year Data						
Has treated supplier	0.20	0.40	0.00	0.00	1.00	23,761
Customer treated (2010)	0.01	0.11	0.00	0.00	1.00	23,761
Total assets (billion USD)	12.96	45.13	1.30	0.00	362.08	23,480
Revenues (billion USD)	5.25	13.63	0.76	0.00	90.74	23,433
Net income/Assets	-0.07	0.40	0.03	-2.61	0.43	18,696
EBITDA/Assets	0.02	0.35	0.10	-2.09	0.51	20,126
COGS/Assets	0.60	0.68	0.38	0.00	3.72	20,161
ΔPPE/Assets	0.02	0.10	0.00	-0.21	0.60	20,019
Mean supplier U.S.-wide emission intensity	155.85	307.37	30.63	0.00	1771.01	6,431
Sum supplier U.S.-wide emissions	14111.11	28636.88	1209.56	0.00	151793.55	6,431
Goods and services scope 3 emissions	1708.08	4830.20	160.48	0.17	34010.03	4,035
Goods and services scope 3 emission intensity	68.13	111.32	27.43	0.04	716.20	4,035

This table contains summary statistics for the main variables of interest. The sample period is from 2010 to 2017. Panel A contains statistics for the entire sample of customer-supplier-year observations. This sample is obtained from merging FactSet Revere data on customer-supplier pairs, EPA data on facility-level emissions, and Compustat data on financial information about suppliers. Panels B and C contain summary statistics for supplier-year and customer-year observations in our base sample, respectively. Refer to Table A2 in Appendix for variable definitions. All continuous variables are winsorized at the 1 and 99% level.

Table 2: T-tests on Unmatched Sample

	Mean Non-Treated	Mean Treated	Diff
Supplier size	7.739	11.268	-3.528***
	(0.004)	(0.014)	(0.024)
Obs.	345,117	10,288	
Supplier profitability	0.071	0.107	-0.036***
	(0.000)	(0.001)	(0.002)
Obs.	328,325	10,287	
Supplier debt	0.250	0.337	-0.087***
	(0.000)	(0.002)	(0.002)
Obs.	343,320	10,237	
Supplier Tobin Q	1.981	1.527	0.455***
	(0.002)	(0.006)	(0.014)
Obs.	311,591	10,145	
Supplier R&D stock	0.396	0.092	0.303***
	(0.001)	(0.001)	(0.008)
Obs.	345,693	10,306	

This table contains t-tests for the main covariates of interest, and between the control and treated groups, over the entire sample period from 2010 to 2017. Standard errors are in parenthesis. * corresponds to p<.10, ** to p<0.05 and *** to p<0.01.

Table 3: Summary Statistics on Matched Sample

	Mean	Std. Dev.	Median	Min	Max	Obs.
Ending	0.18	0.39	0.00	0.00	1.00	82,555
Starting	0.26	0.44	0.00	0.00	1.00	82,555
Relationship length (years)	3.74	2.94	3.00	1.00	15.00	82,555
Number of customers	31.86	35.44	21.00	1.00	237.00	82,555
Number of suppliers	20.67	39.60	8.00	2.00	269.00	82,555
Supplier treated 2010	0.09	0.28	0.00	0.00	1.00	82,555
Supplier total assets (Billion USD)	30.99	82.92	2.89	0.01	531.86	82,288
Supplier profitability	0.08	0.17	0.11	-0.80	0.34	82,194
Supplier debt	0.26	0.20	0.23	0.00	0.99	81,953
Supplier R&D stock	0.49	0.91	0.17	0.00	5.51	82,555
Customer total assets (billion USD)	68.05	119.89	23.14	0.02	1027.62	38,185

This table contains summary statistics for the main variables of interest computed on the matched sample. The matching approach is described in Section 3.2. The sample period is from 2010 to 2017. All continuous variables are winsorized at the 1 and 99% level. Refer to Table A2 in Appendix for variable definitions.

Table 4: Probability of Termination and Cap-and-Trade Program: Baseline

	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.016	0.061***	0.053**	0.047**	0.025**
	(0.012)	(0.021)	(0.021)	(0.022)	(0.010)
Supplier size			0.012	0.014	0.087***
			(0.019)	(0.021)	(0.019)
Supplier profitability			-0.072	-0.104*	-0.008
			(0.057)	(0.060)	(0.051)
Supplier debt			-0.112	-0.137*	-0.215***
			(0.076)	(0.083)	(0.045)
Supplier Tobin Q			0.017	0.017	0.007
			(0.015)	(0.015)	(0.006)
Supplier R&D stock			-0.037*	-0.038*	0.039***
			(0.020)	(0.021)	(0.014)
Relationship length			0.004	0.004	0.002**
			(0.003)	(0.003)	(0.001)
Matched supplier	Yes	Yes	Yes	Yes	
Matched supplier competitor group					Yes
Excl. treated customers				Yes	
Supplier sector × Year FE	Yes				
Supplier FE	Yes	Yes	Yes	Yes	
Customer × Year FE		Yes	Yes	Yes	
Customer × Year × Competitor group FE					Yes
Supplier × Competitor group FE					Yes
Obs.	82,552	82,555	75,801	70,822	112,644
R^2	0.171	0.830	0.837	0.842	0.828

The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. The regression is estimated on the matched supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25 thousand tons of CO2e in California in 2010 are excluded. In column (5), each treated supplier is compared to all of its direct competitors over the entire sample period, including other potentially treated competitors. Robust standard errors adjusted for supplier-level clustering in columns (1)-(4) and supplier-competitor group in column (5) are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to p<.10, ** to p<0.05 and *** to p<0.01.

Table 5: Probability of Termination and Cap-and-Trade Program: Treatment Intensity

	(1)	(2)	(3)	(4)	(5)
Intensity of Treatment × Post	0.001**	0.009***	0.008***	0.008**	0.003*
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)
Supplier size			0.013	0.015	0.084***
			(0.019)	(0.021)	(0.019)
Supplier profitability			-0.067	-0.098*	-0.011
			(0.054)	(0.056)	(0.051)
Supplier debt			-0.089	-0.113	-0.214***
			(0.066)	(0.072)	(0.045)
Supplier Tobin Q			0.010	0.012	0.006
			(0.011)	(0.012)	(0.006)
Supplier R&D stock			-0.033**	-0.034**	0.037***
			(0.016)	(0.017)	(0.014)
Relationship length			0.003	0.003	0.002**
			(0.002)	(0.003)	(0.001)
Matched supplier	Yes	Yes	Yes	Yes	
Matched supplier competitor group					Yes
Excl. treated customers				Yes	
Customer × Year FE		Yes	Yes	Yes	
Supplier sector × Year FE	Yes				
Supplier FE	Yes	Yes	Yes	Yes	
Customer × Year × Competitor group FE					Yes
Supplier × Competitor group FE					Yes
Obs.	82,552	82,555	75,801	70,822	112,644
R^2	0.171	0.831	0.838	0.842	0.828

The table contains the regression results for Equation 1. The treatment dummy is substituted by a continuous variable describing each supplier's intensity of treatment as of 2010 (and equal to 0 for the control group). This value is then standardized by its standard deviation. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. The regression is estimated on the matched supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25 thousand tons of CO_2e in California in 2010 are excluded. In column (5), each treated supplier is compared to all of its direct competitors over the entire sample period, including other potentially treated competitors. Robust standard errors adjusted for supplier-level clustering in columns (1)-(4) and supplier-competitor group in column (5) are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 6: Probability of Termination and Cap-and-Trade Program: Robustness

	(1) Alt. sd. err. cluster	(2) Alt. treat.	(3) Excl. geo-div suppl.	(4) Excl. const. suppl.	(5) Cond. logit	(6) Placebo CA	(7) Placebo Spillover
Treatment × Post	0.053***		0.055**	0.101*	0.373***		
	(0.014)		(0.024)	(0.058)	(0.118)		
Treatment					-0.330***		
					(0.115)		
Treatment 2012 × Post		0.024*					
		(0.014)					
HQ CA × Post						0.010	
						(0.017)	
US Climate Alliance × Post							-0.022
							(0.042)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes		Yes	Yes
Matched sample					Yes		
Supplier FE	Yes	Yes	Yes	Yes		Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier sector FE					Yes		
Obs.	75,801	70,607	69,173	14,974	49,042	83,529	5,810
R^2	0.837	0.884	0.753	0.894		0.506	0.760

The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. Controls are supplier size, profitability, Tobin Q, R&D stock and relationship length. In column (1) the table reports estimates using standard errors clustered at the pair level. In column (2), the treatment is allocated according to firms' 2012 emissions in their facilities in California. In column (3), treated suppliers are not geographically diversified (i.e., they only produce emissions in California in the pre-treatment period). In column (4), treated suppliers are not financially constrained, using the composite financial constraint indicator proposed by Bartram et al. (2022). In column (5) the table reports the estimates of the conditional logit regression on the sub-sample underlying column (2) in the baseline Table 4. In column (6) the placebo group *HQ CA* consists of firms headquartered in California, albeit not being treated. Suppliers with placebo treatment (i.e., with headquarters in California) are matched to control observations according to the matching approach described in Section 3.2. In column (7), the placebo treatment group consists of control suppliers that in 2010 produce emissions above 25 thousand tonnes of CO2 equivalents in U.S. states that are part of the UN Climate Alliance at its onset in 2017. The empirical approach follows von Meyerinck et al. (2021). These suppliers are matched to further control observations according to the matching approach described in Section 3.2. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). Excluding column (1) –where standard errors are clustered at the pair level– and column (7) –where they are estimated using non-parametric bootstrap– standard errors are clustered at the supplier level. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 7: Probability of Starting New Relationship and Cap-and-Trade Program

	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.043***	-0.090***	-0.094***	-0.102***	-0.027*
	(0.016)	(0.022)	(0.023)	(0.022)	(0.014)
Supplier size			-0.015	-0.020	0.055***
			(0.023)	(0.024)	(0.013)
Supplier profitability			0.113*	0.105*	-0.029
			(0.060)	(0.063)	(0.045)
Supplier debt			0.028	0.028	0.179***
			(0.046)	(0.047)	(0.048)
Supplier Tobin Q			0.015***	0.014***	0.013**
			(0.005)	(0.005)	(0.006)
Supplier R&D stock			0.013	0.011	0.046***
			(0.016)	(0.017)	(0.016)
Matched supplier	Yes	Yes	Yes	Yes	
Matched supplier competitor group					Yes
Excl. treated customers				Yes	
Customer × Year FE		Yes	Yes	Yes	
Supplier sector × Year FE	Yes				
Supplier FE	Yes	Yes	Yes	Yes	
Customer × Year × Competitor group FE					Yes
Supplier × Competitor group FE					Yes
Obs.	82,552	82,555	75,801	73,416	112,644
R^2	0.249	0.858	0.861	0.863	0.863

The table contains the regression results for the specification reported in Equation 2. The dependent variable takes a value of 1 if the relationship between a given supplier and its customer is observed in time t but not in time $t-1$, and 0 otherwise. The regression is estimated on the matched supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25 thousand tons of CO2e in California in 2010 are excluded. In column (5), each treated supplier is compared to all of its direct competitors over the entire sample period, including other potentially treated competitors. Robust standard errors adjusted for supplier-level clustering in columns (1)-(4) and supplier-competitor group in column (5) are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 8: Probability of Termination and Cap-and-Trade Program: Competitiveness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI Industry		Lerner Index Industry		HHI Competitor Group		Number of Competitors	
	High	Low	High	Low	High	Low	Few	Many
Treated × Post	0.009	0.096***	0.016	0.093***	0.014	0.036**	0.015	0.037**
	(0.021)	(0.032)	(0.023)	(0.034)	(0.013)	(0.015)	(0.012)	(0.015)
Supplier size	0.047*	-0.013	0.006	0.013	0.109***	0.079***	0.066***	0.105***
	(0.027)	(0.023)	(0.027)	(0.020)	(0.034)	(0.023)	(0.021)	(0.031)
Supplier profitability	-0.056	-0.002	-0.109	-0.016	-0.061	0.010	0.059	-0.050
	(0.081)	(0.042)	(0.116)	(0.038)	(0.089)	(0.062)	(0.074)	(0.070)
Supplier debt	0.012	-0.081*	-0.129	-0.045	-0.341***	-0.151***	-0.245***	-0.191***
	(0.062)	(0.043)	(0.114)	(0.035)	(0.085)	(0.051)	(0.053)	(0.069)
Supplier Tobin Q	-0.007	0.004	0.012	0.004	0.033**	-0.000	-0.002	0.013*
	(0.008)	(0.006)	(0.018)	(0.005)	(0.014)	(0.006)	(0.009)	(0.008)
Supplier R&D stock	0.018	-0.039**	-0.053	-0.021	0.058*	0.035**	0.032*	0.048**
	(0.019)	(0.015)	(0.036)	(0.015)	(0.034)	(0.016)	(0.019)	(0.020)
Relationship length	-0.000	0.004**	0.004	0.005***	0.003**	0.001	0.003**	0.001
	(0.002)	(0.002)	(0.005)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Matched supplier	Yes	Yes	Yes	Yes				
Matched supplier competitor group					Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes				
Supplier FE	Yes	Yes	Yes	Yes				
Customer × Year × Competitor group FE					Yes	Yes	Yes	Yes
Supplier × Competitor group FE					Yes	Yes	Yes	Yes
Obs.	42,678	26,437	47,742	22,064	48,128	64,516	52,674	59,970
R^2	0.871	0.833	0.860	0.725	0.838	0.819	0.820	0.834

The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 as long as it continues. The regression is estimated on matched sub-samples supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. In column (1), suppliers are in a relatively concentrated sector (average pre-treatment SIC 3-digits sector HHI above the pre-treatment median). In column (2), suppliers are in a relatively competitive sector (average pre-treatment SIC 3-digits sector HHI below the pre-treatment median). In columns (3) and (4), suppliers are in SIC 3-digits sectors with average pre-treatment Lerner Index above and below the pre-treatment median, respectively. In columns (5) and (6), suppliers are in a group of matched competitors with average pre-treatment HHI above or below the pre-treatment median. In columns (7) and (8), suppliers have a mean pre-treatment number of matched competitors in their group below or above the pre-treatment median. Robust standard errors clustered at the supplier level in columns (1) to (4) and at the supplier-competitor group level in columns (5) to (8) are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to p<.10, ** to p<0.05 and *** to p<0.01.

Table 9: Probability of Termination and Cap-and-Trade Program: Input Specificity

	Panel A			
	(1) Specialized input	(2) Standardized input	(3) Above median R&D	(4) Below median R&D
Treated × Post	-0.003	0.062**	0.020	0.072**
	(0.016)	(0.031)	(0.025)	(0.029)
Controls	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes
Obs.	41,406	21,171	38,641	30,857
R^2	0.892	0.829	0.836	0.856

	Panel B			
	(1) US pair	(2) US supplier-Foreign customer pair	(3) Above median length of rel.	(4) Below median length of rel.
Treated × Post	0.046**	0.053*	-0.036	0.054**
	(0.018)	(0.028)	(0.024)	(0.027)
Controls	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes
Obs.	40,683	32,138	19,524	50,743
R^2	0.782	0.878	0.860	0.867

The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. The regression is estimated on matched sub-samples supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. In column (1) of Panel A, the analysis is conducted on the sub-sample of suppliers in a specialized sector (according to the classification provided by Giannetti et al., 2011). In column (2), the analysis is conducted on the sub-samples of suppliers in a standardized sector (according to the same classification). In columns (3) and (4), the analysis is conducted on the sub-samples of suppliers with an average R&D over total assets throughout the pre-treatment period above and below the pre-treatment sample median, respectively. In column (1) of Panel B, the analysis is conducted on the sub-sample of pairs in which both the supplier and the customer are headquartered in the U.S. In column (2), the analysis is conducted on the sub-sample of pairs in which the supplier is headquartered in the U.S. and the customer is headquartered abroad. In column (3), the analysis is conducted on the sub-sample of pairs having a length of relationship in year t above the median total relationship length of all the pairs in the sample. In column (4), the analysis is conducted on the sub-sample of pairs with a length of relationship below the sample's median. Robust standard errors clustered at the supplier level are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to p<.10, ** to p<0.05 and *** to p<0.01.

Table 10: Supplier's Real Effects of Cap-and-Trade Program

	Panel A					
	(1) COGS/Assets	(2) COGS/Assets	(3) log(Assets)	(4) log(Assets)	(5) ΔPPE/Assets	(6) ΔPPE/Assets
Treated × Post	0.017	0.047**	-0.114*	-0.423***	0.003	-0.035*
	(0.014)	(0.019)	(0.061)	(0.057)	(0.017)	(0.021)
Specialized × Treated × After		-0.038		0.399***		0.031
		(0.025)		(0.065)		(0.021)
Matched supplier	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,968	8,432	10,008	8,463	9,961	8,434
R^2	0.855	0.860	0.986	0.989	0.422	0.426

	Panel B					
	(1) Net Income/Assets	(2) Net Income/Assets	(3) EBITDA/Assets	(4) EBITDA/Assets	(5) Log(Revenues)	(6) Log(Revenues)
Treated × Post	-0.049***	-0.109***	-0.026**	-0.061***	-0.020	-0.200***
	(0.016)	(0.021)	(0.013)	(0.016)	(0.048)	(0.036)
Specialized × Treated × After		0.098***		0.043**		0.151***
		(0.023)		(0.017)		(0.054)
Matched supplier	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier Sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	9,789	8,416	9,954	8,420	9,624	8,113
R^2	0.704	0.717	0.792	0.807	0.982	0.986

The table shows the regression results for the specification reported in Equation 3. The regression is estimated on a matched supplier-year panel from 2010 to 2017. The matching approach is described in Section 5.1. The dependent variable in Panel A columns (1) and (2) is the ratio of COGS over lag of total assets; in columns (3) and (4), it is the log of assets; in columns (5) and (6), it is the yearly change in PPE over lag of total assets; in Panel B columns (1) and (2), it is net income over lag of total assets; in columns (3) and (4) it is EBITDA over lag of total assets; in columns (5) and (6) it is log of revenues. Specialized suppliers are categorized according to the classification provided by Giannetti et al. (2011). Robust standard errors clustered at the supplier level are reported in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 11: Customer's Real Effects of Cap-and-Trade Program

	(1)	(2)	(3)	(4)	(5)	(6)
	COGS/Assets	log(Assets)	ΔPPE/Assets	Net Income/Assets	EBITDA/Assets	log(Revenues)
Has treated supplier × Post	-0.021	0.030	-0.004	-0.005	0.001	0.019
	(0.019)	(0.036)	(0.005)	(0.018)	(0.015)	(0.038)
Matched customer	Yes	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes	Yes
Customer sector × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	15,788	15,875	15,644	14,706	15,771	15,367
R^2	0.895	0.980	0.437	0.712	0.798	0.975

The table contains the regression results for the specification reported in Equation 4. The regression is estimated on a matched supplier-year panel from 2010 to 2017. The matching approach is described in Section 5.1. The dependent variable in column (1) is the ratio of COGS over lag of total assets; in column (2) it is the log of assets; in column (3) it is the yearly change in PPE over lag of total assets; in column (4) it is net income over lag of total assets; in column (5) it is EBITDA over lag of total assets; in column (6) it is log of revenues. The sample excludes customers that are directly affected by the California cap-and-trade by having facilities in California that in 2010 emit more than 25 thousand tonnes of CO2 equivalents. Robust standard errors clustered at the customer level are indicated in parentheses. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 12: Probability of Termination and Cap-and-Trade Program: Customers' Climate Transition Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
	Climate Change Awareness		Democrat as of 2016 Elections		US Climate Alliance	
	High	Low	Yes	No	Yes	No
Treated × Post	-0.008	0.065**	-0.048*	0.072*	-0.021	0.059
	(0.019)	(0.027)	(0.026)	(0.038)	(0.026)	(0.044)
Supplier size	0.028	0.010	-0.007	-0.019	0.002	-0.010
	(0.025)	(0.030)	(0.036)	(0.028)	(0.038)	(0.027)
Supplier profitability	-0.143**	0.015	-0.006	-0.012	0.032	-0.011
	(0.058)	(0.087)	(0.101)	(0.092)	(0.112)	(0.089)
Supplier debt	-0.015	-0.142	0.095	-0.033	0.108	-0.030
	(0.063)	(0.110)	(0.070)	(0.072)	(0.076)	(0.073)
Supplier Tobin Q	-0.011	0.006	-0.001	0.010	0.000	0.008
	(0.009)	(0.009)	(0.009)	(0.012)	(0.010)	(0.011)
Supplier R&D stock	-0.030*	-0.009	0.002	-0.041*	0.012	-0.020
	(0.016)	(0.022)	(0.024)	(0.024)	(0.025)	(0.022)
Relationship length	0.001	0.000	0.001	0.005**	0.004	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
Matched supplier	Yes	Yes	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,054	14,630	7,583	11,444	7,478	11,516
R^2	0.822	0.810	0.851	0.800	0.859	0.786

The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. The regression is estimated on matched sub-samples supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.2. In columns (1) and (2), the analysis is conducted on the sub-sample of customers relatively high and low average pre-treatment attention to climate change relative to the pre-treatment median computed at the SIC 2-digit and HQ country level (Sautner et al., 2023 construct the proxy for customers' attentiveness to climate change, the data is available at Sautner et al., 2020). In columns (3) and (4), the analysis is conducted on the sub-sample of customers with headquarters in democratic or republican states as per their 2016 elections. In columns (5) and (6), the analysis is conducted on the sub-sample of customers with headquarters in states members of the U.S. Climate Alliance and in the remaining states respectively (according to the data and approach provided by von Meyerinck et al., 2021, members of the U.S. Climate Alliance at the onset of the coalition, in 2017, are California, Colorado, Connecticut, Delaware, Hawaii, Massachusetts, Minnesota, New York, North Carolina, Oregon, Rhode Island, Vermont, Virginia, and Washington; democrat states are California, Connecticut, Delaware, Hawaii, Illinois, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, Vermont, Washington). Refer to Table A2 in Appendix for variable definitions. Robust standard errors clustered at the supplier level are reported in parentheses. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

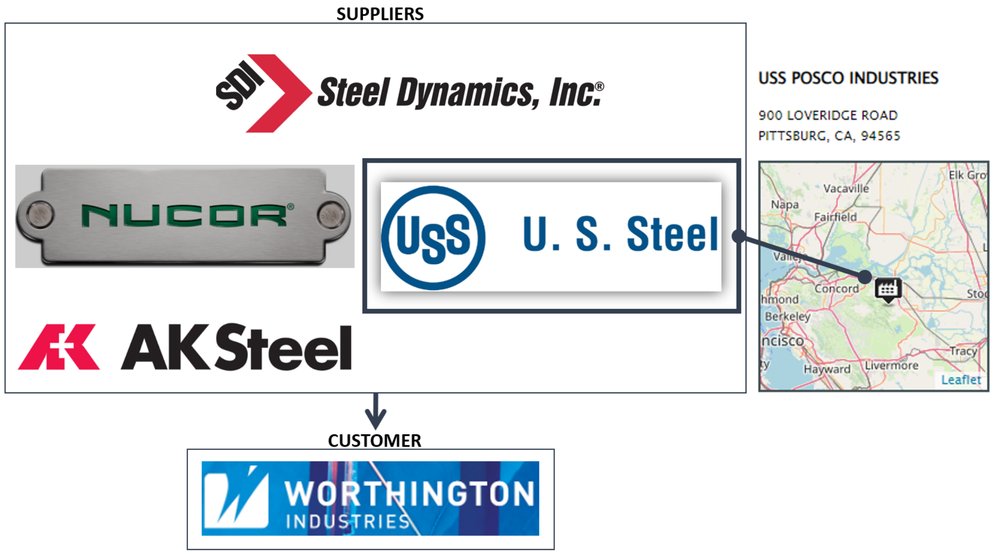
Table 13: Environmental Effects of Cap-and-Trade Program

Panel A				
	(1) U.S.-Wide Emissions	(2) U.S.-Wide Emission Intensity	(3) Scope 1-2 Emissions	(4) Scope 1-2 Emission Intensity
Treated × Post	6663.909***	143.707*	715.372	75.214
	(1824.427)	(86.434)	(800.458)	(60.426)
Matched supplier	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes
Supplier Sector × Year FE	Yes	Yes	Yes	Yes
Obs.	2,055	2,052	889	889
R^2	0.959	0.990	0.972	0.986

Panel B				
	(1) U.S. Supply Chain Emissions	(2) U.S. Supply Chain Emission Intensity	(3) Goods and Services Scope 3	(4) Goods and Services Scope 3 Intensity
Has treated supplier × Post	4470.331***	39.832***	1081.989***	28.252***
	(1400.601)	(15.205)	(368.708)	(10.689)
Matched customer	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes
Customer Sector × Year FE	Yes	Yes	Yes	Yes
Obs.	4,564	4,564	2,487	2,487
R^2	0.831	0.907	0.686	0.735

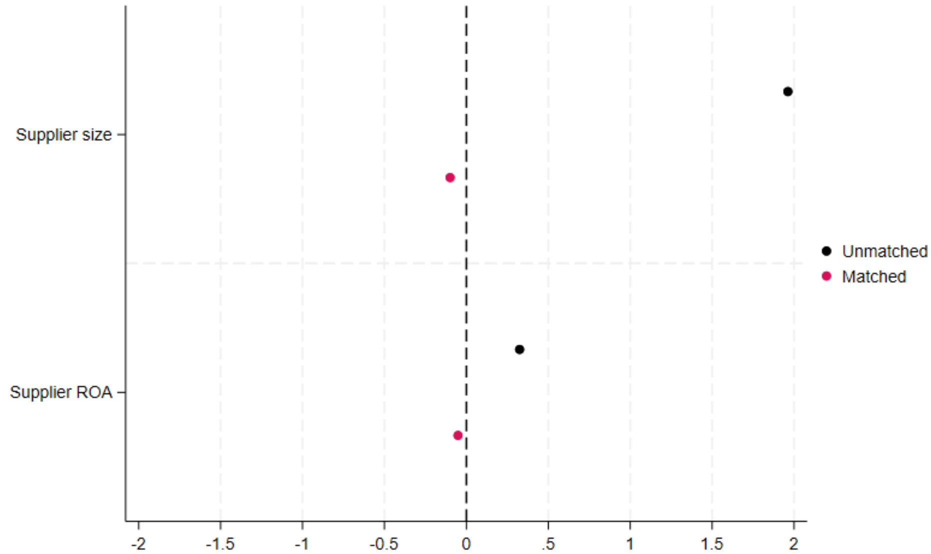
In Panel A, the table shows the regression results for the specification reported in Equation 3. The regression is estimated on a matched supplier-year panel from 2010 to 2017. The matching approach is described in Section 5.1. The dependent variable in column (1) is a firm's U.S.-wide emissions obtained grouping EPA facility-level emissions at the firm parent level. In column (2) it is emission intensity computed as the firm's total U.S.-wide emissions divided by its total assets. The dependent variable in column (3) is a firm's total scope 1 and 2 emissions reported to CDP. In column (5), it is CDP reported scope 1 and 2 emission intensity. In Panel B, the table shows the regression results for the specification reported in Equation 4. The regression is estimated on a matched customer-year panel from 2010 to 2017. The matching approach is described in Section 5.1. The sample in Panel B excludes customers directly affected by the California cap-and-trade. The dependent variable in column (1) is the total U.S.-wide direct supply chain emissions, in column (2) it is the average U.S.-wide emission intensity of each customer's supplier (in other words, we compute the average U.S.-wide emission divided by total assets of the direct suppliers of a given customer). In column (3), the dependent variable is the ICE Climate Transition Finance inferred scope 3 upstream emissions (emissions of "goods and services" purchased), in column (4) it is the ICE Climate Transition Finance inferred scope 3 upstream emission intensity. The use of inferred emission is motivated by the scarce availability of reported scope 3 upstream emissions data. In 2010, this variable is available for 15 observations in our sample, in 2011 for 37 and in 2012 for 39. Standard errors are indicated in parentheses, they are clustered at the supplier level in Panel A and at the customer level in Panel B. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Figure 1: Illustration of the Structure of the Dataset



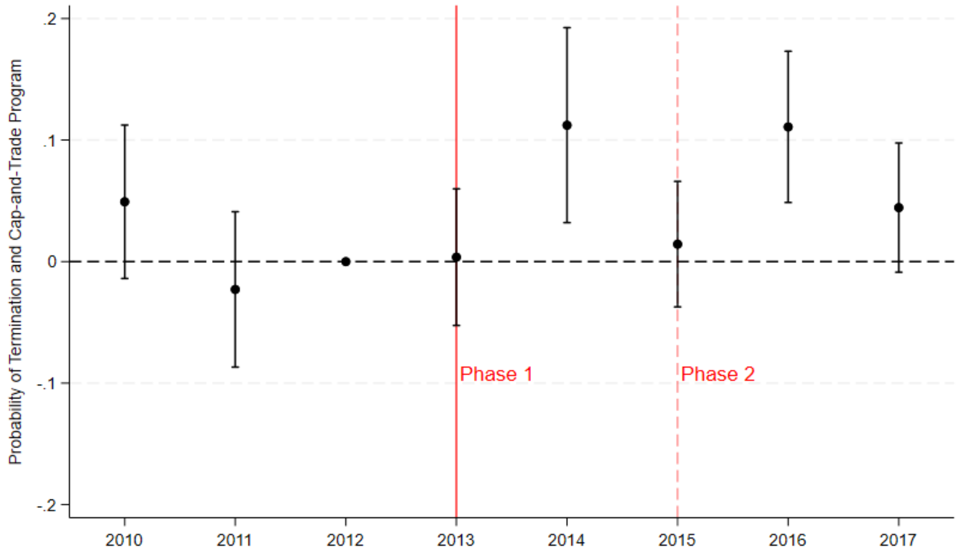
This figure illustrates the structure of the dataset through the example of the treated supplier U.S. Steel and its customer Worthington Industries. According to the EPA FLIGHT data, the U.S. Steel POSCO facility mapped close to San Francisco on the right-hand side of the figure produced sufficient emissions to be subject to the cap-and-trade. We map this facility to its owner, U.S. Steel. U.S. Steel is a supplier of Worthington Industries, visualized at the bottom of the figure, and a direct competitor of other suppliers of the same company (i.e., Steel Dynamics, NUCOR and AK Steel, visualized in the left-hand side of the figure). Our final dataset follows supplier-customer pairs such as U.S. Steel-Worthington Industries or NUCOR-Worthington Industries over time.

Figure 2: Matching Performance



This figure shows the performance of the propensity score weighting estimator. Specifically, for each propensity score weighting variable, the figure shows the standardized difference in mean between control and treated groups.

Figure 3: Identifying Assumption



These figures show the parallel trends preceding the introduction of the Californian cap-and-trade (2013) and the dynamic effect of the event on treated firms' probability to continue a business relationship with their customers. The bars define the 95% confidence interval around the coefficient, represented by the dot. The first vertical line defines the beginning of phase 1 of carbon trading, it starts in 2013 for electricity production and import, and for industrial firms having plants in California that produce more than 25 thousand tons of CO2 equivalents. The second vertical line defines the beginning of phase 2 of the cap-and-trade when the regulatory framework is extended to include distributors of petroleum and natural gas in California.

Online Appendix

Table A1: Excerpts from Treated Suppliers' SEC Filings: Anecdotal Evidence

Treated supplier	SEC filings excerpts
Air Products and Chemicals Inc.	"Some of the Company's operations are within jurisdictions that have or are developing regulatory regimes governing emissions of greenhouse gases (GHG). [...] As of 1 January 2013, The Company's hydrogen production facilities in California and the EU will begin their compliance obligation under California's AB32 cap and trade program and Phase 3 EU ETS, respectively; however, these facilities have contractual terms to enable cost recovery. Increased public concern may result in more international, U.S. federal, and/or regional requirements to reduce or mitigate the effects of GHG. Although uncertain, these developments could increase the Company's costs related to consumption of electric power, hydrogen production, and fluorinated gases production. The Company believes it will be able to mitigate some of the increased costs through its contractual terms, but the lack of definitive legislation or regulatory requirements prevents accurate estimate of the long-term impact on the Company. Any legislation that limits or taxes GHG emissions could impact the Company's growth, increase its operating costs, or reduce demand for certain of its products." Air Products and Chemicals Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/2969/000119312512476878/d409668d10k.htm
Alon USA Partners LP	"Climate change legislation or regulations restricting emissions of greenhouse gases could result in increased operating costs and a reduced demand for our refining services. [...] In addition, the federal Congress has from time to time considered adopting legislation to reduce emissions of GHGs, and a number of the states have already taken legal measures to reduce emissions of GHGs primarily through the planned development of GHG emission inventories and/or regional GHG cap and trade programs. The adoption of legislation or regulatory programs to reduce emissions of GHGs could require us to incur increased operating costs, such as costs to purchase and operate emissions control systems, to acquire emissions allowances or comply with new regulatory or monitoring and reporting requirements or result in reduced demand for refined petroleum products we produce. One or more of these developments could have an adverse effect on our business, financial condition and results of operations." Alon USA Partners LP, Form 10-K https://www.sec.gov/Archives/edgar/data/1556766/000155676615000012/aldw-20141231x10k.htm
Altagas LTD	"As of December 31, 2017, all of AltaGas' operating natural gas-fired power generation facilities in California were in material compliance with their air permit requirements, which are issued in accordance with federal and state emissions standards. Costs associated with meeting AB 32 and California's cap-and-trade program have been passed through to the utilities pursuant to the applicable PPA." Altagas LTD, Annual Information Form https://www.sec.gov/Archives/edgar/data/1695519/000104746918004451/a2235909zex-4_1.htm

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Treated supplier	SEC filings excerpts
California Steel Industries Inc.	"The United States government or various governmental agencies have introduced or are contemplating regulatory changes in response to the potential impacts of climate change. International treaties or agreements may also result in increasing regulation of greenhouse gas emissions, including the introduction of carbon emissions trading mechanisms. Any such regulation regarding climate change and greenhouse gas, or GHG emissions could impose significant costs on our steelmaking operations and on the operations of our customers and suppliers, including increased energy, capital equipment, environmental monitoring and reporting and other costs in order to comply with current or future laws or regulations concerning and limitations imposed on our operations by virtue of climate change and GHG emissions laws and regulations. The potential costs of "allowance," "offsets" or "credits" that may be part of potential cap-and-trade programs or similar future regulatory measures are still uncertain. Any adopted future climate change and GHG regulations could negatively impact our ability (and that of our customers and suppliers) to compete with companies situated in areas not subject to such limitations. From a medium and long-term perspective, we are likely to see an increase in costs relating to our assets that emit significant amounts of greenhouse gases as a result of these regulatory initiatives. These regulatory initiatives will be either voluntary or mandatory and may impact our operations directly or through our suppliers or customers. Until the timing, scope and extent of any future regulation becomes known, we cannot predict the effect on our financial condition, operating performance and ability to compete." California Steel Industries Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/751799/000119312511075101/d10k.htm
Campbell Soup Company	"Increased compliance costs and expenses due to the impacts of climate change and additional legal or regulatory requirements regarding climate change that are designed to reduce or mitigate the effects of carbon dioxide and other greenhouse gas emissions on the environment may cause disruptions in, or an increase in the costs associated with, the running of our manufacturing facilities and our business, as well as increase distribution and supply chain costs. Moreover, compliance with any such legal or regulatory requirements may require us to make significant changes in our business operations and strategy, which will likely require us to devote substantial time and attention to these matters and cause us to incur additional costs. [...] The effects of climate change and legal or regulatory initiatives to address climate change could have a long-term adverse impact on our business and results of operations." Campbell Soup Company, Form 10-K https://www.sec.gov/Archives/edgar/data/16732/000001673223000109/cpb-20230730.htm
DTE Energy Company	"The purchase of emission credits from market sources, higher costs of purchased power, and the retirement of facilities where control equipment is not economical. We would seek to recover these incremental costs through increased rates charged to our utility customers as authorized by the MPSC." DTE Energy Company, Form 10-K https://www.sec.gov/Archives/edgar/data/936340/000093634015000014/dteenergy2014123110k.htm
Forterra Inc.	Climate change and climate change legislation or regulations may adversely impact our business. [...] it seems clear that changes to regulate carbon emissions are a key focus for the Biden Administration and other governmental entities, including California, which has had a cap and trade system in place since 2012. In light of the uncertainty around what regulations will be implemented, we cannot at this time reasonably predict what the costs of any future compliance requirements may be, but it is likely our costs will increase in relation to any climate change legislation and regulation concerning greenhouse gases, which could have an adverse effect on our future financial position, results of operations or cash flows." Forterra Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/1678463/000167846322000020/frta-20211231.htm

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Treated supplier	SEC filings excerpts
Freeport-McMoRan Copper & Gold Inc	"California Air Resources Board (CARB) has developed "cap and trade" regulations [...] Some of our operations in California are subject to these regulations, which require us to purchase offsets and allowance instruments. The total amount of instruments we must purchase will vary annually. While we do not expect these costs to be material, similar or more onerous state regulations could substantially increase our costs. [...] From a medium and long-term perspective, we may experience increased costs relating to our greenhouse gas emissions as a result of regulatory initiatives in the U.S. and other countries in which we operate. In addition, the cost of electricity that we purchase from others may increase if our suppliers incur increased costs from the regulation of their greenhouse gas emissions. Although we have modeled different scenarios, we cannot predict the magnitude of increased costs with any certainty given the wide scope of potential regulatory changes in the many countries in which we operate. Increased regulation of greenhouse gas emissions may also reduce demand for the oil and gas we produce." Freeport-McMoRan Copper & Gold Inc, Form 10-K https://www.sec.gov/Archives/edgar/data/831259/000083125914000006/a2013form10-k.htm
Lockheed Martin Corporation	"The increasing global regulatory focus on greenhouse gas (GHG) emissions and their potential impacts relating to climate change could result in laws, regulations or policies that significantly increase our direct and indirect operational and compliance burdens, which could adversely affect our financial condition and results of operations. These laws, regulations or policies could take many forms, including carbon taxes, cap and trade regimes, increased efficiency standards, GHG reduction commitments, incentives or mandates for particular types of energy or changes in procurement laws. Changes in government procurement laws that mandate or take into account climate change considerations, such as the contractor's GHG emissions GHG emission reduction targets, lower emission products or other climate risks, in evaluating bids could result in costly changes to our operations or affect our competitiveness on future bids, or our ability to bid at all. In addition to incurring direct costs to implement any climate-change related laws, regulations or policies, we may see indirect costs rise, such as increased energy or material costs, as a result of policies affecting other sectors of the economy. Although most of these increased costs likely would be recoverable through pricing, to the extent that the increase in our costs as a result of these policies are greater than our competitors we may be less competitive on future bids or the total increased cost in our industry's products and services could result in lower demand from our customers." Lockheed Martin Corporation, Form 10-K https://www.sec.gov/Archives/edgar/data/936468/000093646823000009/lmt-20221231.htm
Martin Marietta Materials Inc.	The company anticipates that any increased operating costs or taxes relating to GHG emission limitations at the Woodville operation or for magnesium hydroxide produced at the Manistee operation would be passed on to its customers. The magnesium oxide products produced at the Manistee operation compete against other products that emit a lower level of GHGs in their production. Therefore, the Manistee facility may be required to absorb additional costs due to the regulation of GHG emissions in order to remain competitive in pricing in that market." Martin Marietta Materials Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/916076/000119312514064999/d654417d10k.htm
Martin Marietta Materials Inc.	"The Company expects that the number of free allowances allocated to Riverside Cement will not be sufficient to cover all of its GHG emissions, but it will be unable to determine the total number of allowances that Riverside Cement will be required to purchase for any year until the year ends and its total GHG emissions for the period are determined. Riverside Cement has begun to purchase allowances to cover GHG emissions that it expects will exceed its free allowances. In addition to the cost of purchasing allowances, Riverside Cement also expects that its energy costs will increase due to the impact of these regulations on the electric utility industry." Martin Marietta Materials Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/916076/000119312515060008/d877241d10k.htm

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Treated supplier	SEC filings excerpts
Praxair Inc.	"Hydrogen production plants and a large number of other manufacturing and electricity-generating plants have been identified under California law as a source of carbon dioxide emissions and these plants have also become subject to recently promulgated cap-and-trade regulations in that state. Praxair believes it will be able to mitigate the costs of these regulations through the terms of its product supply contracts. However, legislation that limits GHG emissions may impact growth by increasing operating costs and/or decreasing demand." Praxair Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/884905/000088490513000011/pxq4201210k.htm
Texas Industries Inc.	"Implementation of federal and state laws and regulations, changes in laws or regulations or permits, or discovery of currently unknown conditions could increase our cost of compliance, require additional capital expenditures, reduce or shut down production or hinder our ability to expand or build new production facilities. [...] We expect to incur additional costs because of these regulations. In addition to the cost of purchasing allowances, we also expect that our energy costs will increase due to the impact of these regulations on the electric utility industry. The California cement industry is discussing a number of issues with CARB, including a California border adjustment mechanism to help create a level playing field with imported cement, but it is uncertain whether such a mechanism will be implemented. The validity of the law and rules remains under attack in several lawsuits, the results of which remain uncertain. As a result of these and other uncertainties, at this time we cannot predict the ultimate cost or effect of the rules on our business." Texas Industries Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/97472/000009747213000023/a2013053110k.htm
United Airlines Inc.	"State of California's cap and trade regulations, environmental taxes for certain international flights, limited greenhouse gas reporting requirements and land-use planning laws which could apply to airports and could affect airlines in certain circumstances. In addition, there is the potential for additional regulatory actions in regard to the emission of greenhouse gases by the aviation industry. The precise nature of future requirements and their applicability to the Company are difficult to predict, but the financial impact to the Company and the aviation industry would likely be adverse and could be significant." United Airlines Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/319687/000119312514060695/d624298d10k.htm
United States Steel Corporation	Steel producers in the United States, along with their customers and suppliers, are subject to numerous federal, state and local laws and regulations relating to the protection of the environment. Steel producers in Canada and the EU are also subject to similar laws. These laws continue to evolve and are becoming increasingly stringent. The ultimate impact of complying with such laws and regulations is not always clearly known or determinable because regulations under some of these laws have not yet been promulgated or are undergoing revision. Environmental laws and regulations, particularly the CAA, could result in substantially increased capital, operating and compliance costs. International environmental requirements vary. While standards in the EU, Canada and Japan are generally comparable to U.S. standards, other nations, particularly China, have substantially lesser requirements that may give competitors in such nations a competitive advantage [...] GHG policies could negatively affect our results of operations and cash flows." United States Steel Corporation, Form 10-K https://www.sec.gov/Archives/edgar/data/1163302/000119312513061613/d448577d10k.htm
USG Corporation	"From time to time, legislation has been introduced proposing a "carbon tax" on energy use or establishing a so-called "cap and trade" system. Such legislation would almost certainly increase the cost of energy used in our manufacturing processes. If energy becomes more expensive, we may not be able to pass these increased costs on to purchasers of our products. It is difficult to accurately predict if or when currently proposed or additional laws and regulations regarding emissions and other environmental concerns will be enacted or what capital expenditures might be required as a result of them. Stricter regulation of emissions might require us to install emissions control or other equipment at some or all of our manufacturing facilities, requiring significant additional capital investments." USG Corporation, Form 10-K www.sec.gov/Archives/edgar/data/757011/000075701113000023/usg-12312012x10k.htm

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Treated supplier	SEC filings excerpts
Valero Energy Corporation	"Governmental restrictions on greenhouse gas emissions – including so-called "cap-and-trade" programs targeted at reducing carbon dioxide emissions – could result in material increased compliance costs, additional operating restrictions or permitting delays for our business, and an increase in the cost of, and reduction in demand for, the products we produce, which could have a material adverse effect on our financial position, results of operations, and liquidity. [...] Complying with AB 32, including the LCFS and the cap-and-trade program, could result in material increased compliance costs for us, increased capital expenditures, increased operating costs, and additional operating restrictions for our business, resulting in an increase in the cost of, and decreases in the demand for, the products we produce. To the degree we are unable to recover these increased costs, these matters could have a material adverse effect on our financial position, results of operations, and liquidity." Valero Energy Corporation, Form 10-K https://www.sec.gov/Archives/edgar/data/1035002/000103500214000008/vloform10-kx12312013.htm
Waste Connections Inc.	"Generally, the promulgation of climate change laws or regulations restricting or regulating greenhouse gas, or GHG, emissions could increase our costs to operate. The EPA's current and proposed regulation of GHG emissions may adversely impact our operations. In 2009, the EPA made an endangerment finding allowing GHGs to be regulated under the CAA. The CAA requires stationary sources of air pollution to obtain New Source Review, or NSR, permits prior to construction and, in some cases, Title V operating permits. Pursuant to the EPA's rulemakings and interpretations, certain Title V and NSR Prevention of Significant Deterioration, or PSD, permits issued on or after January 2, 2011, must address GHG emissions. As a result, new or modified emissions sources may be required to install Best Available Control Technology to limit GHG emissions. The EPA's recently adopted Subpart XXX also requires the reduction of GHG emissions from new or modified landfills, and the Guidelines, known as Subpart Cf, published by the EPA in August 2016, will require the reduction of GHG emissions from existing landfills. In addition, the EPA's Mandatory Greenhouse Gas Reporting Rule sets monitoring, recordkeeping, and reporting requirements applicable to certain landfills and other entities. [...] Certain states and many Canadian provinces have promulgated regulations and rules to limit GHG emissions through requirements of specific controls, carbon levies, cap and trade programs or other measures. These rules will affect not only our business, but also that of our customers." Waste Connections Inc., Form 10-K https://www.sec.gov/Archives/edgar/data/1318220/000114420417011069/v457710_10k.htm

The table shows excerpts of the SEC filings of a sub-sample of treated suppliers. The excerpts provide anecdotal evidence of the impacts of the California cap-and-trade policy on suppliers' financial performance and economic activity.

Table A2: Variable Definitions

Variable Name	Description and Source
Ending	Dummy variable equal to 1 if the relationship between supplier and customer is not observed in $t+1$ and 0 otherwise (Customer-Supplier-Year level, Constructed, FactSet).
Starting	Dummy variable equal to 1 if the relationship between supplier and customer is observed for the first time in t and 0 otherwise (Customer-Supplier-Year level, Constructed, FactSet).
Relationship Length (Years)	Length of the relationship from the first time in which the customer-supplier pair is observed in FactSet to t (Customer-Supplier-Year level, Constructed, FactSet).
Number of Customers	Number of sample customers of each given sample supplier (Supplier-Year level, Constructed, FactSet).
Number of Suppliers	Number of sample suppliers of each given sample customer (Customer-Year level, Constructed, FactSet).
Supplier Treated (2010)	Dummy equal to 1 if the supplier produced more than 25,000 metric tons of CO2 equivalents in one of its California facilities in 2010, 0 otherwise (Supplier level). Computed as: $\mathbf{1}_s(CAEmissions_{2010} > 25kCO2e)$ (Constructed, EPA, FactSet).
Supplier Treated (2012)	Dummy equal to 1 if the supplier produced more than 25,000 metric tons of CO2 equivalents in one of its California facilities in 2012, 0 otherwise (Supplier level). Computed as: $\mathbf{1}_s(CAEmissions_{2012} > 25kCO2e)$ (Constructed, EPA, FactSet).
Supplier HQ in California	Dummy equal to 1 if the supplier's headquarters are in California, 0 otherwise (Supplier level, Constructed, FactSet).
Customer Treated (2010)	Dummy equal to 1 if the customer produced more than 25,000 metric tons of CO2 equivalents in one of its California facilities in 2010, 0 otherwise (Customer level). Computed as: $\mathbf{1}_c(CAEmissions_{2010} > 25kCO2e)$ (Constructed, EPA, FactSet).
Has Treated Supplier	Dummy equal to 1 if the customer has at least one supplier including and after 2013 that has produced at least 25,000 metric tons of CO2 equivalents in its California facilities in 2010 (Customer level, Constructed, EPA, FactSet).
Supplier US-Wide Emissions	Total emissions produced by EPA facilities owned by the supplier in the US (Supplier-Year level, Constructed, EPA, FactSet).
Log of supplier US Emissions	Log of total emissions produced by EPA facilities owned by the supplier in the US (Supplier-Year level, Constructed, EPA, FactSet).
Supplier US Emission Intensity	Total emissions produced by the supplier in its EPA facilities located in the US, divided by the total assets of the supplier (*at*, Supplier-Year level, Constructed, EPA, FactSet, Compustat).
Supplier California Emissions	Total emissions produced by EPA facilities owned by the supplier in California (Supplier-Year level, Constructed, EPA, FactSet).
Supplier California Emissions (2010)	Total emissions produced by EPA facilities owned by the supplier in California in 2010 (Supplier level, Constructed, EPA, FactSet).
Supplier California (CA) Emission Intensity Std.	Total emissions produced by the supplier in 2010 in its EPA facilities located in California, divided by the total assets of the supplier and standardized by the standard deviation of this measure across the sample (Supplier level). Computed as: $\frac{CAEmissions{>}25ktCO2e_{s,2010}}{STD_{2010} \times Totalassets_{i,2010}}$. The variable is set to 0 when the observation is missing. (Constructed, EPA, FactSet, Compustat).
Suppliers' Emissions	Sum of emissions produced by the sample suppliers of each customer in their US EPA facilities (Customer-Year level, Constructed, EPA, FactSet).
Suppliers' Average Emissions	Emissions produced by the average sample supplier of each customer in its US EPA facilities (Customer-Year level, Constructed, EPA, FactSet).
Suppliers' Average Emission Intensity	US emission intensity of the average sample supplier of each customer (Customer-Year level, Constructed, EPA, FactSet).
Suppliers Emitting in US Climate Alliance States	Dummy equal to 1 if the supplier produced more than 25,000 metric tons of CO2 equivalents in its plants located in one of the States that joined the US Climate Alliance in its founding year (2017) excluding California (the states are Colorado, Connecticut, Delaware, Hawaii, Massachusetts, Minnesota, New York, North Carolina, Oregon, Rhode Island, Vermont, Virginia, and Washington), 0 otherwise (Supplier level, von Meyerinck et al. (2021), FactSet, EPA).

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Variable Name	Description and Source
Supplier Geographically Diversified	Dummy equal to 1 if the supplier produced emissions outside California in the pre-treatment period, 0 otherwise (Supplier level, Constructed and based on Bartram et al. (2022), FactSet, EPA).
Supplier Financially Constrained	Dummy equal to 1 if the supplier is financially constrained according to at least 4 of 6 alternative financial constraints measure defined by Bartram et al. (2022), 0 otherwise (Supplier level, Constructed and based on Bartram et al. (2022), FactSet, EPA).
Customer CC Attention Above Median	Dummy equal to 1 if the customer scores an average pre-treatment climate change attention in its *firm-level climate change exposure* measure above the pre-treatment median computed at the SIC 2-digits and headquarters country level, 0 otherwise (Customer level, Constructed, Sautner et al. (2020), FactSet).
Supplier Producing Specialized Input	Dummy equal to 1 if the supplier is in a SIC 2-digits sector that is classified as *differentiated input*, 0 otherwise (Industry level, Constructed, Giannetti et al. (2011), FactSet, Compustat).
HHI (Supplier SIC 3-dgt.)	HHI computed at the SIC 3-digit sector as $sum(market\ share^2)$ where *market share = sale/industry sale* (Industry-Year level, Constructed, Compustat).
HHI (Supplier Comp. Group)	HHI computed within the competitor group of each treated supplier as *sum of market share*^{2} where *market share = sale/comp. group sale* (Competitors' groups level, Constructed, FactSet, Compustat).
Lerner Index (Supplier SIC 3-dgt.)	Lerner Index computed at the SIC 3-digit sector as the average *ni / sale* for North American suppliers and *ib + xi + do / sale* for other suppliers and capped between 0 and 1 (Industry-Year level, Constructed, Compustat).
Supplier Size	*log of at* (Supplier-Year level, Constructed, Compustat).
Supplier Profitability	ROA computed as *EBITDA / at* (Supplier-Year level, Constructed, Compustat).
Supplier Debt	Total debt computed as *(dltt + dlc) / at* (Supplier-Year level, Constructed, Compustat).
Supplier Tobin Q	Tobin Q computed as *at + market value - be) / at* where *market value = csho × prcc f* (Supplier-Year level, Constructed, Compustat).
Supplier R&D Stock	Stock of R&D computed as the sum of *xrd* over time from 2005 to time *t*, assuming *xrd = 0* when the observation is missing, over *at* (Supplier-Year level, Constructed, Compustat).
Supplier Cash	*ch / at* (Supplier-Year level, Constructed, Compustat).
Supplier COGS / Assets	*cogs / 1-year lag at* (Supplier-Year level, Constructed, Compustat).
Supplier Log(Revenues)	*log of revt* (Supplier-Year level Constructed, Compustat).
Supplier Net Income / Assets	*ni / 1-year lag at* for North American suppliers and *(ib + xi + do) / 1-year lag at* for other suppliers (Supplier-Year level, Constructed, Compustat).
Supplier EBITDA / Assets	*EBITDA / 1-year lag at* (Supplier-Year level, Constructed, Compustat).
Supplier ΔPPE / Assets	Yearly change in supplier *ppe* in levels, over 1-year lagged *at* (Supplier-Year level, Constructed, Compustat).
Scope 1-2 Emissions	Scope 1-2 emissions reported by the supplier to CDP (Supplier-Year level, ICE Climate Transition Finance, CDP).
Scope 1-2 Emissions Inf.	Scope 1-2 emissions of the supplier inferred by the data provider (Supplier-Year level, ICE Climate Transition Finance, CDP).
Customer Size	*log of at* (Customer-Year level, Constructed, Compustat).
Customer Profitability	ROA computed as *EBITDA / at* (Customer-Year level, Constructed, Compustat).
Customer Debt	Total debt computed as *dltt + dlc* (Customer-Year level, Constructed, Compustat).
Customer COGS / Assets	*cogs / 1-year lag at* (Customer-Year level, Constructed, Compustat).
Customer Log(Revenues)	*log of revt* (Customer-Year level, Constructed, Compustat).
Customer Net Income / Assets	*ni / 1-year lag at* for North American customers and *(ib + xi + do) / 1-year lag at* for other customers (Customer-Year level, Constructed, Compustat).
Customer EBITDA / Assets	*EBITDA / 1-year lag at* (Customer-Year level, Constructed, Compustat).
Customer ΔPPE / Assets	Yearly change in customer *ppe* in levels, over 1-year lagged *at* (Customer-Year level, Constructed, Compustat).
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Variable Name	Description and Source
Goods and Services Scope 3 Emissions	Scope 3 emissions inferred by the data provider and associated with the goods and services used by the firm (Customer-Year level, ICE Climate Transition Finance).

The table contains the description of the variables used in the analysis. In the sources, Compustat refers to both Compustat Global and Compustat North America. Every variable obtained from Compustat Global is retrieved in its original currency and then converted to USD using annual average exchange rates. Annual averages are computed on monthly exchange rates retrieved from IBES through WRDS.

Table A3: Probability of Termination and Cap-and-Trade Program: Matching Robustness

	(1) Unmatched	(2) P.S.W. incl. debt	(3) P.S.W. incl. controls	(4) P.S.M. stringent	(5) P.S.W. stringent
Treated × Post	0.029**	0.069***	0.070***	0.031**	0.041***
	(0.014)	(0.023)	(0.024)	(0.016)	(0.015)
Supplier size	0.020**	0.026	0.052***	0.034*	0.068***
	(0.010)	(0.017)	(0.020)	(0.017)	(0.023)
Supplier profitability	-0.023	-0.077*	-0.059	-0.020	-0.076
	(0.029)	(0.041)	(0.043)	(0.044)	(0.052)
Supplier debt	-0.028	-0.073	-0.117**	-0.030	-0.087*
	(0.026)	(0.051)	(0.048)	(0.039)	(0.048)
Supplier Tobin Q	-0.005	0.003	0.006	-0.001	0.004
	(0.004)	(0.007)	(0.007)	(0.004)	(0.005)
Supplier R&D stock	-0.004	-0.015	-0.003	-0.008	-0.004
	(0.008)	(0.011)	(0.012)	(0.011)	(0.013)
Supplier cash			0.061		
			(0.064)		
Relationship length	0.007***	0.004***	0.005***	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Alternative matching		Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes
Obs.	246,355	75,801	71,815	50,325	50,218
R^2	0.362	0.840	0.829	0.401	0.576

The table shows the regression results for the baseline specification reported in Equation 1 using alternative matching approaches. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. *P.S.W.* stands for propensity score weighting, *P.S.M.* stands for propensity score matching. In column (1), the regression is estimated on an unmatched supplier-customer pair-year panel from 2010 to 2017. In column (2), the regression is estimated by filtering for suppliers headquartered in the United States and using an exact match for suppliers' SIC 2-digits sector and a propensity score weighting approach based on suppliers' pre-treatment size, profitability and debt. The maximum weight allocated to each supplier is extended to the entire sample period from 2010 to 2017. Using the nearest neighbor algorithm, we select at least three controls for each treated supplier. In column (3) we expand the previous propensity score weighting approach to additionally include suppliers' Tobin's Q, R&D stock and cash. In column (4), we filter for suppliers headquartered in the United States and we adopt an exact match based on suppliers' SIC 2-digits sector and customer-by-year and a propensity score match based on suppliers' pre-treatment size and profitability. Using the nearest neighbor algorithm, we select at least one control for each treated supplier. In column (5), we adopt the same approach but rather than relying on a propensity score matching we weight the observations extending the maximum pre-treatment propensity score weight of each supplier to the entire sample from 2010 to 2017. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). Robust standard errors adjusted for supplier-level clustering. Refer to Table A2 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.