Rewiring Supply Chains Through Climate Policy*

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Abstract

We show that climate transition risks can significantly disrupt supply chain networks. Specifically, suppliers affected by the California cap-and-trade program are more likely to lose customer relationships and less likely to form new ones. The effects are more pronounced for suppliers facing high competitive pressure and producing standardized inputs, indicating a loss of competitiveness due to the program. Affected suppliers also experience a drop in revenues, assets, and profitability. This supply chain rewiring is consistent with carbon leakage, as customers exposed to the program through production networks exhibit increased supply chain emissions intensity, highlighting the unintended consequences of uncoordinated climate policies.

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1 Introduction

As part of the transition to a low-carbon economy, many governments have implemented carbon pricing programs to curb emissions, resulting in a patchwork of climate regulations across countries and jurisdictions. These uncoordinated climate policies can lead to different forms of environmental regulatory arbitrage or carbon leakage. For instance, previous research finds that companies react to heterogeneous climate policies by relocating production and emissions from facilities in jurisdictions with regulated (higher) carbon prices to those in jurisdictions with unregulated (lower) carbon prices (Ben-David, Jang, Kleimeier, and Viehs, 2021; Bartram, Hou, and Kim, 2022). However, carbon leakage can also occur through changes in the supply chain, which can be triggered by the increased production costs faced by regulated local suppliers. In fact, to exploit the heterogeneity of the climate policies in existence, customers might shift their sourcing to unregulated (foreign) suppliers (Cosbey, Droege, Fischer, and Munnings, 2019). In turn, this can affect business relationships, trade patterns, and emissions production along supply chains.

In this paper, we empirically examine how environmental policies affect supply chains. Specifically, we investigate whether suppliers suffer the termination of their existing customer relationships as they compete with other suppliers in jurisdictions without carbon pricing policies in place. In addition, we assess how carbon pricing policies affect firms' financial and environmental performance, focusing on scope 3 carbon emissions.

It is not immediately clear whether heterogeneous carbon pricing policies result in the termination of supply chain relationships. On the one hand, higher carbon prices lead to a permanent increase in input costs of affected firms (Ryan, 2012), placing them at a disadvantage compared to their competitors.[1] Thus, the introduction of climate policies increases

[1]For instance, Air Products and Chemicals Inc., in its Securities and Exchange Commission (SEC) 10K filings, notes 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" (available at https://www.sec.gov/Archives/edgar/data/2969/000119312512476878/d409668d10k.htm).

firms' exposure to climate transition risks (Greenstone, 2002), which, when affecting suppliers, can heighten the risk of supply chain disruptions.[2] On the other hand, regulators often mitigate the impact of environmental policies on firm competitiveness by granting exemptions to highly energy-intensive and trade-exposed sectors (Fowlie, Reguant, and Ryan, 2016). There might be other factors impacting supply chain relationships. High switching costs, such as those related to search efforts or supplier specificity (Barrot and Sauvagnat, 2016; Bernard, Moxnes, and Saito, 2019), generally increase the stickiness of supply chains. Also, the anticipation of future supply chain emissions regulations (Ramadorai and Zeni, 2024), or pressure from environmentally conscious stakeholders and consumers (Krueger, Sautner, and Starks, 2020; Aghion, Bénabou, Martin, and Roulet, 2023) may reduce the incentive to cut ties with suppliers subject to climate policies.

To analyze the effect of carbon pricing policies on supply chains, we focus on suppliers subject to the California cap-and-trade program, the second-largest cap-and-trade program globally, and the only cap-and-trade policy that regulates industrial emissions in the United States. Implemented in 2013, this program sets a cap on emissions for firms that produce more than 25,000 tons of carbon dioxide equivalents at their California facilities. California provides an ideal setting to examine the effects of carbon pricing programs on supply chains, as no other U.S. states regulate industrial emissions, thus offering a unique context of within-country policy heterogeneity. This setting allows us to study whether customers terminate or maintain relationships with suppliers affected by the cap-and-trade program while simultaneously engaging in new relationships with similar suppliers not subject to the program.

We employ a difference-in-differences (DiD) methodology combined with a matching ap-

[2]For instance, Campbell Soup Company, in its SEC 10K filings, notes 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." (available at https://www.sec.gov/Archives/edgar/data/16732/000001673223000109/cpb-20230730.htm).

proach to analyze changes in the likelihood of terminating an existing relationship or initiating a new one with a supplier affected by the cap-and-trade program. The introduction of California's cap-and-trade program increases the marginal costs for suppliers with polluting operations in the state. To identify suppliers subject to the program (hereafter *treated suppliers*), we combine facility-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 group of otherwise similar suppliers based on industry, firm size, and profitability (hereafter *control suppliers*). Additionally, our methodology incorporates customer-by-time fixed effects to control for unobserved shocks affecting customers' demand for suppliers' products. Given our identification strategy, we assess the likelihood that the same customer terminates its relationship with a treated supplier compared to a control supplier within the same year.

Our baseline results indicate that treated suppliers experience a 5.1 percentage point increase in the likelihood of terminating their existing customer relationships compared to control suppliers following the introduction of the cap-and-trade program. This result is economically significant, representing a 25% higher probability of terminating a relationship with suppliers subject to the program (compared to the unconditional probability of 20%).

We further find that following the introduction of the carbon program, the likelihood of initiating a new relationship with a supplier subject to the cap-and-trade is about 8.4 percentage points lower compared to control suppliers. This result is economically significant, representing a 29% lower probability of initiating a relationship with suppliers subject to the program (compared to the unconditional probability of 29%). These findings suggest that the baseline results are not solely driven by adjustments within the existing customer base of suppliers impacted by the policy. Rather, they indicate a broader restructuring of the entire supply chain to mitigate exposure to increasing climate transition risks.

One concern regarding our interpretation of the results is that the higher probability

of terminating relationships with suppliers subject to the cap-and-trade program might be driven solely by a reshuffling of their customer base. For example, Bartram et al. (2022) show that financially constrained suppliers often shift their operations to plants in other states, which could naturally lead them to establish new relationships with customers located near their non-Californian facilities. We alleviate this concern by showing that our baseline results remain both economically and statistically significant even within the sub-sample of suppliers that operate exclusively in California, as well as in the sub-sample of financially unconstrained suppliers.

Next, we test whether the loss of competitiveness experienced by firms under the carbon pricing program drives our results. This hypothesis predicts that the effects should be stronger for firms operating in more competitive industries. Indeed, customers can more effectively mitigate climate transition risk in their supply chains by switching to alternative suppliers in industries with high product substitutability. Consistent with this notion, we find that our baseline effects are more pronounced among suppliers operating in more competitive industries, as proxied by a low Herfindahl-Hirschman Index (HHI), a low Lerner Index, and less concentrated groups of direct competitors (as identified in FactSet Revere). Likewise, we expect customers facing low switching costs to more readily and cheaply source their inputs from alternative suppliers. Consistent with this prediction, we find that our effects are concentrated among suppliers offering standardized inputs and those with lower investment in innovation (i.e., research and development, or R&D, expenditures). The results are also stronger among suppliers with weaker connections to their customers, as indicated by greater geographical distance and shorter relationship duration.

To further investigate the economic mechanism underlying our results, we provide firm-level evidence suggesting that the program's introduction impairs the competitiveness of treated suppliers relative to their competitors, due to increased exposure to climate transition

risks.[3] We find that treated suppliers experience larger declines in revenues, assets, and profitability, along with a greater increase in costs of goods sold (COGS), compared to control suppliers. Additionally, we find that the deterioration of financial performance is more pronounced for suppliers producing standardized inputs. These findings align with those of Greenstone (2002) and Ryan (2012), indicating that firms producing standardized inputs face a higher likelihood of disruptions. This increased risk may prompt customers to switch suppliers to mitigate the impact of climate transition shocks.

We then explore whether customers' anticipation of future environmental regulations outside of California might mitigate the observed effects. Even with the risk of supply chain disruptions, customers under pressure to decarbonize their supply chain may opt to maintain relationships with suppliers subject to the cap-and-trade program to enhance their prospect of lower scope 3 emissions. Supporting this idea, we find that customers headquartered in environmentally conscious jurisdictions—such as Democrat-led states and customers reporting relatively high attention to climate transition risks in the pre-program period (as proxied by the index of climate change attention in Sautner, Van Lent, Vilkov, and Zhang, 2023) are also less likely to terminate relationships with suppliers subject to the program.

Finally, we examine the environmental implications of the cap-and-trade program. We observe that the program's introduction does not significantly reduce the total emission intensity (scope 1 and 2 emissions relative to assets) of affected suppliers compared to control suppliers. Furthermore, consistent with carbon leakage, we find an increase in customers' emissions along the supply chain. We find an increase in the supply chain (scope 3) emission intensity of firms sourcing from at least one treated supplier compared to otherwise similar firms following the program's implementation. These findings highlight the unintended con-

[3]For instance, United States Steel Corporation, in its SEC 10K filings, 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" (available at https://www.sec.gov/Archives/edgar/data/1163302/000119312513061613/d448577d10k.htm).

sequences of the California cap-and-trade program, aligning with the primary carbon leakage mechanisms outlined by Cosbey, Droege, Fischer, and Munnings (2019).

Our paper contributes to several strands of the literature. First, we add to the literature on carbon leakage. Empirical studies suggest that differences in climate policies across regions can incentivize firms to increase pollution outside the regions subject to those policies (Benincasa, Kabas, and Ongena, 2022; Duchin, Gao, and Xu, 2022; Ivanov, Kruttli, and Watugala, 2024; Laeven and Popov, 2023). Related to our work, Ben-David et al. (2021) and Bartram et al. (2022) provide evidence of within-firm reallocation of production to facilities outside carbon-regulated jurisdictions. Our paper builds on this literature by identifying a different mechanism of carbon leakage, specifically through supply chain realignment, and by uncovering the unintended financial and environmental consequences of this leakage.

We also contribute to the literature on the effects of shocks on production networks (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012; Jiang, Rigobon, and Rigobon, 2021; Baldwin and Freeman, 2022; Acemoglu and Tahbaz-Salehi, 2024), focusing on the network effects of the introduction of cap-and-trade programs. Demir, Javorcik, Michalski, and Ors (2024) examine the effects of import taxes on production networks using customer-supplier links, and Devulder and Lisack (2020) explore the impact of carbon taxes using input-output data. We contribute to this literature using a micro-level approach focusing on supplier-customer relationships to study the effects of heterogeneous cap-and-trade programs across regions. Our findings also complement research on the propagation of corporate social responsibility (CSR) and environmental, social, and governance (ESG) practices along the supply chain (Schiller, 2018; Dai, Liang, and Ng, 2021b; Dai, Duan, Liang, and Ng, 2021a; Asgharian, Dzieliński, Hashemzadeh, and Liu, 2023; Bisetti, She, and Zaldokas, 2023; Hege, Li, and Zhang, 2023; Lu, Peng, Shin, and Yu, 2023; Homroy and Rauf, 2024).

Our paper also relates to research on the impact of physical climate risks on supply chains. Barrot and Sauvagnat (2016) find that suppliers affected by major natural disasters lead to

output losses for their clients, especially when they produce a specific input, and Carvalho et al. (2021) show that downstream propagation explains a sizable fraction of the decline in gross output following the Great East Japan Earthquake of 2011. Pankratz and Schiller (2023) show that suppliers experiencing heat days above expectations are more likely to suffer the termination of their customer relationships. In contrast, our study focuses on climate transition risks, particularly those arising from state-level environmental policies. This focus allows us to analyze carbon leakage and uncover the unintended environmental consequences of these policies. Unlike physical climate risks or ESG shocks, the environmental policy we examine produces a more permanent impact on firms' production processes.

Last, we contribute to the literature exploring how climate regulations impact 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 study shows that carbon pricing programs can influence firms' performance and drive a reconfiguration of production networks to circumvent the regulations.

2 Institutional background

2.1 The California cap-and-trade program

There is broad consensus among economists that the most effective way to reduce global carbon emissions is through carbon pricing programs. As a result, many jurisdictions have implemented carbon taxes or cap-and-trade systems to promote a transition to a low-carbon economy.

In line with this approach, California enacted Assembly Bill 32 in 2006, setting a target to reduce emissions to 1990 levels by 2020. As part of this commitment, the California cap-and-trade program was introduced in January 2013. During its first phase, from 2013 to

2014, the program targeted electricity generation (including imports) and industrial facilities emitting more than 25,000 tons of carbon dioxide (CO2) equivalents annually. In 2015, the program was expanded to include petroleum and natural gas distributors.

Under California's cap-and-trade program, regulated facilities must surrender permits corresponding to their emissions. A portion of these permits is allocated for free, while the remainder is auctioned quarterly and traded in a permits market. The specific allocation of free permits at the plant level remains undisclosed. However, according to the California Air Resources Board, from 2013 to 2017, the free allocation of permits was designed to cover, on average, approximately 85% of the emissions produced by a theoretical industrial facility under the program.[4] The requirement to surrender emission permits is based on emissions produced in previous years. Therefore, the program's effects are expected to be significantly observable only from the first year after its implementation or subsequent amendments. In 2013, the average supplier subject to the policy produced 2.6 million tons of CO2 equivalents in its California facilities. The auction price of permits was $10 per metric ton of CO2 equivalents in 2013, averaging approximately $12.50 from 2013 to 2017.

2.2 Carbon leakage

The adoption of carbon policies such as the California cap-and-trade program is influenced by each jurisdiction's unique economic, political, social, and environmental circumstances. This results in considerable variation in the implementation of such policies across regions and countries. The uneven landscape of carbon policies, characterized by partial geographical coverage, creates opportunities for shifting emissions from regions with high carbon pricing to those with lower or no carbon pricing, a phenomenon known as "carbon leakage".

The literature has identified several channels through which carbon leakage can occur (Cosbey et al., 2019). One of the most prominent is the *competitiveness channel*, which

[4]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).

has been extensively discussed in prior research (see, for example, the comprehensive review by Fowlie et al., 2016). According to this channel, high carbon prices raise production costs in regions with environmental regulations, reducing the competitiveness of the affected producers and giving a comparative advantage to firms in regions without such regulations. In response to the decreased competitiveness and the potential for increased supply chain uncertainty, downstream customers and final consumers may shift 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 to international trade flows due to incomplete environmental policies affecting energy prices in California. This risk is particularly significant in energy-intensive and trade-exposed industrial sectors. To mitigate these carbon leakage concerns, the program provides exemptions for certain highly exposed entities, and a substantial body of literature has examined the potential impact of border carbon adjustment mechanisms designed to level the playing field between firms operating under different environmental policies (Fowlie, Petersen, and Reguant, 2021).[5]

Building on this conceptual framework, we conduct an empirical analysis at the supply chain level. Using supply chain data, we investigate how the introduction of California's cap-and-trade program impacts the likelihood of firms regulated by the program losing customers to competitors outside the regulated area and establishing new business relationships.

3 Methodology and data

This section outlines our empirical strategy, describes the sample, and defines the variables.

[5]Other channels include the market channel, where reduced demand for carbon in regulated jurisdictions lowers global fossil fuel prices, thereby increasing demand in unregulated areas (e.g., Harstad, 2012); the income channel, where carbon taxes alter relative prices and wages across regions, impacting the terms of trade and potentially leading to mixed effects on consumption and emissions outside the regulated area; and the technology spillovers channel, where higher carbon prices incentivize investment and innovation in low-carbon technologies, ultimately reducing emissions.

3.1 Empirical strategy

Our primary empirical strategy examines whether the introduction of the California cap-and-trade program has led to a rewiring of supply chains outside the state's boundaries. Specifically, we test whether suppliers subject to the program are more likely to have their customer relationships terminated vis-a-vis other suppliers not subject to the program.

To determine whether changes in customer relationships are attributable to the cap-and-trade program, our methodology exploits both the program's implementation timing and the suppliers it affects. We employ a difference-in-differences approach, comparing changes in the likelihood of relationship termination between treatment and control groups around the program's enactment in 2013 (the treatment year). Specifically, we estimate the following linear probability model at the pair-year level:

$$Ending_{i,j,t+1} = \beta Treated_i \times Post_t + \gamma_1' X_{i,t} + \gamma_2 z_{i,j,t} + \mu_i + \eta_{j,t} + \epsilon_{i,j,t}. \quad (1)$$

where $Ending_{i,j,t+1}$, is a dummy variable that takes the value one if the relationship between supplier i and customer j ends in a given year (i.e., it is not observed in year $t+1$), and zero if the relationship is observed in year t and continues into $t+1$. We account for mergers and acquisitions, delistings, and bankruptcies by excluding supplier-customer pairs that end their relationship in the same year as one of the firms exits the Compustat sample. $Treated_i$ is a dummy variable that takes the value of one for suppliers i that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents at the onset of the EPA emission disclosure policy in 2010. $Post_t$ is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise.

$X_{i,t}$ includes controls for suppliers' size (logarithm of total assets), profitability (return on assets defined as EBITDA-to-lagged assets ratio), leverage (short and long-term debt-to-assets ratio), Tobin's Q, and R&D stock (sum of past R&D expenditures-to-assets ratio). $z_{i,j,t}$ accounts for the duration of the supplier-customer relationship, measured across the

entire FactSet sample, including the time before the sample period began. These controls address potential correlations between treatment status and firm characteristics (e.g., firms with business activity in California might exhibit unique features like higher profitability) and with the outcome variable (e.g., it may be less desirable to terminate relationships with highly profitable firms). The baseline model is saturated with supplier fixed effects μ_i and customer-by-year fixed effects $\eta_{j,t}$. Robust standard errors are clustered at the supplier level.

We address concerns about reverse causality by defining our treated dummy variable based on data from 2010, three years prior to the implementation of the California cap-and-trade program. Assuming that firms' pre-program supply chain structures represent their optimal configurations, firms would generally have little incentive to alter their supply chains before the program's enactment. By setting the treatment date well in advance of the program's start, we adopt a conservative approach: if some firms in the treatment group reduce their emissions below the regulatory threshold between 2010 and 2012, thereby becoming exempt from the program, any observed negative effect would be diminished, resulting in a weaker estimated effect. Similarly, if firms in the control group increase their emissions above the threshold before the program's implementation, our estimates would also show attenuated effects.

Our main coefficient of interest is the estimate of β. With the inclusion of 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) and those not subject to the program (control) that have a business relationship with the same customer in a given year. This design reduces the likelihood that changes in customer-specific demand drive our results. Therefore, the estimated difference in the probability of termination can be reasonably attributed to supply-side factors. If the program places the affected suppliers at a disadvantage relative to their competitors, we expect β to be positive. Our identification strategy relies on the assumption of parallel trends, meaning that, in the absence of the policy,

the probability of terminating a relationship would have been the same for both treated and control suppliers. This assumption is discussed in detail in Section 4.

3.2 Data sources and sample

To assess the effects of the California cap-and-trade program 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 information on supply chain relationships and competitors from FactSet Revere, which primarily covers publicly listed companies involved in global corporate relationships since 2003. This data set gathers information on supply chain connections and direct business competitors from various sources, including SEC 10-K annual filings, investor presentations, and press releases.

We collect facility-level emissions data from the U.S. Environmental Protection Agency (EPA). Since October 2009, the EPA has maintained the Greenhouse Gas Reporting Program (GHGRP), which provides data on all U.S. establishments emitting 25,000 tons or more of CO2 equivalents annually. These data are publicly accessible through the Program's Facility Level Information on Greenhouse Gases Tool (FLIGHT). We manually merge facility-level emissions data with firm-level information from FactSet using the parent company names provided by the EPA. When parent names do not match, we use facility names for the merge.

Finally, we obtain financial data, along with information on the industries of both customers and suppliers, from the Compustat North America and Global Fundamentals database. We link Compustat data to FactSet using PERMCO identifiers obtained through the Center for Research in Security Prices (CRSP).

Our baseline unmatched sample consists of a panel of 360,735 supplier-customer pair-year

observations from FactSet, including financial information about the suppliers, spanning the period from 2010 to 2017. This sample period enables us to analyze the evolution of supply chains starting from the beginning of the EPA emissions reporting, three years before the California cap-and-trade program's implementation in 2013, and continuing through four years post-implementation. The sample includes 4,726 unique suppliers and 35,059 unique business customers, of which 61 suppliers have at least one facility in California subject to the cap-and-trade program (the treated suppliers). The treated suppliers group includes only U.S. firms. These treated suppliers have a total of 2,409 unique customers. The remaining 4,665 suppliers are not subject to the program. Using data from FactSet Revere, we also identify the direct competitors of the treated suppliers.

Figure 1 illustrates the structure of our data set using the example of a treated firm, U.S. Steel, which owns a facility near San Francisco with emissions sufficient to be regulated under the cap-and-trade program. U.S. Steel, along with its direct competitors—such as Steel Dynamics, NUCOR, and AK Steel—supplies products to Worthington Industries. In some analyses, we compare the time evolution of supplier-customer pairs involving a treated supplier (e.g., the pair U.S. Steel-Worthington Industries) with pairs involving a competitor of the treated supplier selling to the same customer (e.g., NUCOR-Worthington Industries).

To examine the environmental impact of the cap-and-trade program, we enhance our data set by incorporating additional firm-level CO2 emissions data. The data include emissions (scope 1-2) directly reported by firms (sourced from the Carbon Disclosure Project, CDP)[6] as well as emissions (scope 3) estimated by the ICE Climate Transition Finance team (formerly known as Urgentem).[7] We merge these data using the International Securities Identification Number (ISIN) codes of both suppliers and customers. Among our sample suppliers, 501

[6]CDP is a not-for-profit organization that, among other activities targeting the protection of the environment, pushes firms to disclose their scope 1, 2 and 3 emissions and collects the resulting data over time.

[7]Dunz, Emambakhsh, Hennig, Kaijser, Kouratzoglou, and Salleo (2021) provide a detailed explanation of the inference methods used by the data provider.

reported their scope 1 or 2 emissions to the CDP between 2010 and 2017. During the same period, only 216 customers reported their upstream scope 3 emissions (i.e., emissions linked to "goods and services") to the CDP, while ICE estimated upstream scope 3 emissions for 561 customers. Table A1 in the Appendix provides the definitions of these and all other variables used in our study.

3.3 Summary statistics

Table 1 presents summary statistics for the initial (unmatched) sample. Panel A indicates that, on average, about one in five supplier-customer relationships are terminated each year (i.e., the average probability of termination of an existing relationship is 21%). The average probability of initiating a new relationship is 32%. The maximum duration of supplier-customer relationships in our sample is 15 years, with an average duration slightly exceeding three years. This suggests that our study's time window—three years before the implementation of the cap-and-trade program and up to four years after—is adequate to capture both the dynamic effects and their persistence while minimizing potential confounding factors.

3.4 Matched Sample

Table 2 indicates that the treatment and control groups differ significantly across several observable characteristics. To address this, we estimate equation (1) using a matched sample, applying various matching techniques. In our baseline approach, we select treated suppliers and match them based on location (i.e., headquartered in the United States), industry (using two-digit SIC codes), and employ a propensity score weighting approach for firms' pre-treatment size (total assets) and profitability (return on assets, ROA). Each treated supplier is matched, with replacement, to a minimum of three control suppliers using the nearest neighbor algorithm. Figure 2 shows that the standardized differences in means for size and profitability are closer to zero after matching. Table 3 provides summary statistics for our baseline matched sample. The statistics show that the customer-supplier pairs in this

matched sample exhibit characteristics similar to those in the unmatched sample presented in Table 1.

In an alternative matching approach, we compare treated suppliers to their direct competitors as identified in FactSet Revere. Specifically, for each treated supplier, we select its direct competitors throughout the sample period, keeping these competitor groups constant for the analysis. This approach aligns with the assumption that competitor groups remain stable or change slowly over time, allowing us to partially circumvent potential strategic decisions by firms to report or not report certain competitors. Within each competitor group, we select control firms based on propensity score weighting for pre-treatment size and profitability. This method helps mitigate concerns that two-digit SIC codes may not adequately capture the market in which a firm operates.

For specifications using this alternative matching strategy, we replace the baseline fixed effects at the supplier level and customer-by-year level (μ_i and $\eta_{j,t}$ respectively) with supplier-by-competitor group and customer-by-year-by-competitor group fixed effects [$\mu_{g(i)}$ and $\eta_{g(i),j,t}$ respectively, where $g(i)$ identifies the group of direct competitors of each treated firm i]. This approach allows us to examine the effect of interest within the group of each treated supplier's competitors. In other words, we compare the likelihood that a customer terminates its business relationship with a treated supplier after the introduction of the cap-and-trade program to the likelihood of terminating its relationship with a direct competitor of the treated supplier who is not subject to the program.

4 Results

In this section, we present the results of the baseline difference-in-differences regression that examines the restructuring of supply chains in response to the California cap-and-trade program. We then discuss the underlying identifying assumptions and conduct robustness checks to validate our baseline findings. Finally, we explore alternative interpretations for our base-

line results.

4.1 Business relationship termination

Table 4 shows the results of estimating equation (1) on our baseline matched sample with different sets of control variables. In column (1), the regression includes supplier, customer and year fixed effects. The coefficient for the interaction term $Treated \times Post$ is positive and statistically significant at the 10% level, suggesting a higher likelihood of terminating a relationship for treated suppliers relative to controls. This estimate indicates that the cap-and-trade program increases the likelihood of a customer ending its relationship with a policy-affected supplier by 8.2 percentage points compared to a supplier not subject to the program.

In column (2) onwards, we introduce customer-by-year fixed effects, which absorb customer-level demand. The coefficient for the interaction term continues to be positive and statistically significant, while the R^2 of the regression increases significantly from 0.32 to above 0.83. On the one hand, customer-by-year fixed effects reduce our sample by approximately 25% as customers with a single supplier in a given year are not included in the sample (i.e., the sample is restricted to suppliers with at least two business relationships). On the other hand, these regressions absorb potential biases from unobservable customer-level shocks, thereby improving our identification strategy. This setup allows for comparisons between treated suppliers and control suppliers selling to the same customer in a given year.

In column (2), the coefficient of the interaction term $Treated \times Post$ is positive and statistically significant at the 1% level. Column (3) includes additional controls for suppliers and supplier-customer pairs. The coefficient in column (3) is our preferred specification, and it suggests that the cap-and-trade program increases the likelihood of a customer ending its relationship with a California-affected supplier by 5.1 percentage points compared to a supplier not subject to the program. This coefficient is both statistically and economically

significant, indicating a 25% increase relative to the average unconditional probability of terminating a supplier relationship, which is 20% in the matched sample (see Table 2).

In column (4), we exclude from the estimation in column (3) all customers with facilities in California emitting more than 25,000 tons of CO2 equivalents (i.e., treated customers). Although we use fixed effects to control for shocks at the customer-year level, this exclusion further reduces the concern that the observed effect is driven by treated customers instead of treated suppliers. The estimated economic impact is consistent with that in column (3), indicating that customer-by-year fixed effects effectively control for most customer-driven effects and suggesting that the exclusion restriction is valid in our preferred baseline specification shown in column (3).

Last, in column (5), we match each treated supplier with its group of direct competitors and compare treated suppliers with their direct competitors located outside California who share a customer in a given year. The effect of interest remains statistically significant and economically meaningful, indicating an 12% (= 0.023 / 0.20) increase over the average unconditional probability of ending a supplier relationship.

4.2 Identifying assumption

In this section, we test the validity of the identifying assumption underlying our empirical approach. Figure 3 displays the dynamic difference-in-differences effects before and after the introduction of the cap-and-trade program. The coefficients of the interaction term are not statistically different from zero in the years preceding the policy's introduction, suggesting that there are no pre-existing differential trends between treated and control suppliers. The figure also indicates that treated suppliers see an increase in the probability of their existing customer relationships being terminated only after the program is implemented. The coefficient is statistically significant in the years following the introduction in 2013 and the subsequent amendment of the regulation in 2015, respectively. This finding is consistent

with the costs of the policy impacting treated suppliers' performance only after the first year of the program's implementation or any amendments. The cap-and-trade program requires suppliers to purchase allowances annually to cover part of their emissions from the previous year, likely leading to a subsequent restructuring of the supply chain. By 2017, after the termination of several treated supplier-customer relationships in 2014 and 2016, fewer treated supplier-customer relationships remained, making the supply chain restructuring less prevalent.

To further corroborate the validity of our identifying assumption, in the Internet Appendix, we study the annual financial performance of the suppliers in our sample over the period from 2010 to 2017. On the one hand, Figure IA1 shows that suppliers might have acted on their expectation of rising costs due to the cap-and-trade by significantly increasing their inventories over the pre-treatment period between 2010 and 2012, relative to 2013. More importantly, however, Figure IA2 shows that these suppliers' revenues only decreased significantly after 2013, suggesting that their customers did not reduce their business activity with the treated suppliers in anticipation of the policy. These findings further support the validity of our identifying assumption of a significant rewiring away from suppliers subject to the cap-and-trade being observed only after the introduction of the policy.

4.3 Robustness and extensions

Our results so far indicate that the introduction of the California cap-and-trade program leads to an increased probability of treated suppliers experiencing the termination of customer relationships compared to control suppliers. In this section, we test the robustness of our baseline results by using alternative samples and specifications.

Business relationship initiation. We begin by examining possible alternative interpretations of our baseline results. So far, we interpret our baseline results as evidence suggesting

a rewiring of supply chains away from the cap-and-trade program. However, if different customers initiated new relationships with treated suppliers, our baseline results might indicate a shift in the customer base of treated suppliers rather than a broader rewiring of supply chains outside of the California cap-and-trade system.

To explore this alternative interpretation of our results, we examine the probability of initiating new relationships with treated suppliers using a difference-in-differences approach similar to our baseline regression in equation (1). Specifically, we estimate the following linear probability model:

$$Beginning_{i,j,t} = \beta Treated_i \times Post_t + \gamma_1' X_{i,t} + \mu_i + \eta_{j,t} + \epsilon_{i,j,t}, \tag{2}$$

where $Beginning_{i,j,t}$ is a dummy variable that equals one if a relationship between supplier i and customer j is observed in year t but not in year $t-1$, and zero in the subsequent years as long as the relationship is observed in FactSet. We use the same matching approach as in the baseline estimation.

Table 5 shows that suppliers affected by the introduction of the cap-and-trade program are less likely to establish new relationships with customers. This result is consistent across specifications, including those with supplier and customer-by-year fixed effects (both with and without time-varying controls at the supplier level), as well as those with supplier-by-competitor group and customer-by-year-by-competitor group fixed effects. It also holds in a specification that excludes treated customers from the sample.

The coefficient in our preferred specification in column (3) indicates that the cap-and-trade program reduces the likelihood of a customer starting a new relationship with a California-affected supplier by 8.4 percentage points compared to a supplier not subject to the program. This coefficient is both statistically and economically significant, representing a 29% decrease relative to the average unconditional probability of initiating a supplier relationship, which is 29% in the matched sample. Overall, these findings reinforce our interpretation that supply chains are being restructured to avoid the jurisdiction of the California

cap-and-trade program.

Generalized difference-in-differences. Consistent with interpreting the baseline effect as a consequence of the cap-and-trade program, we expect the probability of terminating relationships with treated firms to become more pronounced for suppliers with higher emissions levels in California. Since the intensity of a supplier's treatment is determined by its emissions in California, and the associated costs for affected firms increase with their emissions, we test the robustness of our baseline estimates using a continuous treatment variable that reflects firms' emissions levels in California (above 25,000 tons of CO2 equivalents). To do this, we estimate equation (1) by replacing the dummy variable $Treated_i$ with a continuous treatment variable *Treatment Intensity*$_i$. This measure is calculated as the ratio of a firm's total emissions in California above 25,000 tons of CO2 equivalents in 2010, normalized by the firm's total assets. For ease of interpretation, this measure is standardized by dividing it by its standard deviation. Suppliers in the control group are assigned a value of zero. Consistent with our baseline results, Table IA2 in the Internet Appendix reports positive and statistically significant coefficients for the interaction term, indicating that the probability of terminating a relationship with a treated supplier increases with the intensity of the supplier's emissions in California.

Alternative standard error clustering. In our baseline specification, we cluster standard errors at the supplier level to account for the correlation of standard errors for a given supplier over time. This approach is motivated by the fact that treatment is assigned at the supplier level at the start of the sample period. However, we also perform robustness checks using standard errors clustered at the pair level, consistent with similar empirical strategies in the literature (e.g., Pankratz and Schiller, 2023). Column (1) of Table IA3 in the Internet Appendix indicates that our results remain robust to this alternative clustering approach,

using the specification in column (3) of Table 4.

Alternative treatment dummy variable. Table IA3, column (2), we present baseline results using an alternative method for allocating suppliers into treatment and control groups. In this alternative approach, treated suppliers are defined as those with facilities in California emitting more than 25,000 tons of CO2 equivalents in 2012 (one year before the program's introduction) 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 as in the baseline estimation. Notably, approximately 80% of the treated observations under the baseline definition are also treated in this alternative approach. Although selecting treated suppliers based on emissions from the year before the event raises concerns about potential biases due to anticipatory effects, the baseline results remain robust under this alternative specification.

Suppliers geographically concentrated in California. Table IA3, column (3), presents the estimates of the baseline specification after excluding geographically diversified treated suppliers from the sample. To identify these suppliers, we replicate the firm-level geographical diversification measure used by Bartram et al. (2022). Suppliers that are geographically concentrated in California lack the ability to easily mitigate their exposure to the cap-and-trade program by shifting production to facilities outside of California. The results indicate that geographically concentrated suppliers face a 4.9 percentage point higher increase in the probability of customer relationship termination compared to control suppliers. This suggests that our findings are not solely driven by within-firm reallocation of production to facilities outside of California.

Financially unconstrained suppliers. Table IA3, column (4), presents the estimates of

the baseline specification for a sub-sample consisting exclusively of treated suppliers that are not financially constrained. To identify these suppliers, we replicate the approach proposed by Bartram et al. (2022), classifying firms as financially constrained if they meet at least four of the six financial constraint measures (firm size, dividend payouts, short- and long-term debt ratings, the Kaplan and Zingales, 1997 index, the Whited and Wu, 2006 index, and the Hadlock and Pierce, 2010 index) calculated strictly before the start of the sample period (between 2003 and 2008). This approach allows us to focus on treated suppliers that are less likely to significantly relocate their economic activities to facilities outside of California, aligning with previous evidence of carbon leakage among financially constrained suppliers (Bartram et al., 2022). If within-firm carbon leakage were the sole driver of our results, we would not expect to find a significant effect in the sub-sample of treated suppliers that are not financially constrained. The results confirm that the baseline findings remain robust even within this sub-sample.

Conditional logit. Table IA3, column (5), presents the estimates of the baseline specification using a conditional logit estimator. This approach addresses the concern that using a linear probability model might result in predicted probabilities falling outside the 0-1 interval. For this specification, we use customer-by-year fixed effects and supplier-sector fixed effects. Due to computational constraints, we omit supplier fixed effects, and while the regression is estimated on our matched baseline sample, we do not apply propensity score weighting to the observations. The results are consistent with the baseline findings, with the coefficient of interest remaining positive and statistically significant.

Placebo test. Table IA3, column (6), presents the baseline results using an alternative treatment group. Suppliers are included in this placebo treatment group if they are headquartered in California but do not have facilities in the state emitting more than 25,000 tons

of CO2 equivalents in 2010. Non-treated suppliers in this placebo group are typically "tech firms" headquartered in California such as HP Inc. and DSP Group. These placebo-treated suppliers are matched to non-treated suppliers using the same propensity score weighting approach employed in the baseline estimation. The results indicate that suppliers in the placebo treatment group do not experience a significant increase in the probability of having their pre-existing customer relationships terminated following the introduction of the cap-and-trade program.[8]

Spillover test. Table IA3, column (7), presents the results for an alternative treatment group designed to test whether the introduction of California's cap-and-trade program has spillover effects on suppliers that pollute in different states (i.e., those suppliers in the control group). This approach focuses on suppliers most likely to be affected, excluding those directly impacted by California's cap-and-trade. Specifically, these are suppliers that emit more than 25,000 tons of CO2 equivalents in states that are more likely to adopt similar cap-and-trade measures following California's lead. These states are potentially those that joined the U.S. Climate Alliance with California at its inception in 2017.[9] Suppliers in the baseline matched control group with significant emissions in these states (i.e., emissions exceeding 25,000 tons of CO2 equivalents based on their 2010 EPA reporting) are matched to other control suppliers using the same propensity score weighting methodology applied in the baseline estimation. The findings indicate that suppliers emitting in the U.S. Climate Alliance states do not experience a significant increase in the likelihood of having pre-existing customer relationships terminated. This suggests that customers do not, on average, signifi-

[8]Although these suppliers are headquartered in California and may be affected by the cap-and-trade-induced increase in electricity prices at their headquarters, they do not directly incur all the costs associated with the new environmental policy. As a result, their customers are less likely to have the incentive to reconfigure their supply chains away from these placebo-treated suppliers.

[9]We thank von Meyerinck, Niessen-Ruenzi, Schmid, and Davidoff Solomon (2021) for providing the data and suggesting this empirical approach. The states in the U.S. Climate Alliance in 2017, in addition to California, include Colorado, Connecticut, Delaware, Hawaii, Massachusetts, Minnesota, New York, North Carolina, Oregon, Rhode Island, Vermont, Virginia, and Washington.

cantly restructure their supply chains preemptively, and the cap-and-trade program does not have a significant spillover effect on the control group.

Alternative fixed effects. In our baseline analysis, we saturate the specification model using supplier and customer-by-year fixed effects. Moreover, in our estimation, we account for the possibility of suppliers' sectors affecting our estimates by adopting an exact match at the supplier industry level and by studying the effect within each treated supplier's group of direct competitors, as an alternative proxy for suppliers' sectors. Here, we perform a robustness test by including supplier industry-by-year fixed effects. Column (8) of Table IA3 indicates that our results are not sensitive to the inclusion of a different set of fixed effects.

Intensive margin results. Throughout our analysis, we focus on the extensive margin describing the existence of a relationship between customers and suppliers. This allows us to focus on a larger representative sample of supplier-customer relationships. However, we also perform a robustness test by replicating our analysis at the intensive margin over a relatively smaller sample of supplier-customer relationships for which sales data is available in the Compustat Segment database for the period from 2010 to 2017.[10] Specifically, our dependent variable is the logarithm of the sales of a given supplier to each of its reported customers in a given year. Column (9) of Table IA3 indicates that consistent with our baseline results, for each customer, the sales of treated suppliers experience a greater drop than the sales of control suppliers after the introduction of the cap-and-trade.

Alternative matching approaches. Table IA4 presents the results of the baseline specification estimated using an unmatched sample in column (1) and various alternative matching

[10]This database is exclusively based on the Statements of Financial Standards 14 and 131, which requires publicly listed U.S. firms to disclose the identity of their customers only if the latter represents at least 10% of their total sales.

approaches in columns (2)-(5). Specifically, in column (2), we replicate the propensity score weighting method used in the baseline estimation, augmenting the set of matching controls to include suppliers' leverage. Column (3) further extends this set by incorporating variables that account for the role of cash holdings (cash-to-assets ratio) in mitigating risks associated with supply chain relationships, as suggested by Kulchania and Thomas (2017) as well as investment opportunities (Tobin's Q), and innovation investment (R&D stock). Column (4) applies an exact match based on suppliers' industry and customer-year, along with a propensity score match using pre-treatment size and profitability. Using the nearest neighbor algorithm, we ensure that at least one control is selected for each treated supplier. In column (5), we follow the same matching procedure as in column (4) but additionally weight the observations according to their propensity scores. Across all specifications, the estimated coefficients on the main variable of interest remain positive and statistically significant, indicating that our results are robust to different matching approaches.

5 Economic mechanisms

So far we have established a link between the introduction of the California cap-and-trade program and the restructuring of supply chain networks away from suppliers exposed to the policy. In this section, we explore potential economic mechanisms that could be driving this reorganization of supply chains beyond the scope of the cap-and-trade program.

5.1 Product market competition

When facing the introduction of climate policies affecting their suppliers, customers are arguably more likely to shift their supply chains when the affected suppliers operate in more competitive industries. In these cases, customers can avoid possible supply chain disruptions arising from the cap-and-trade by selecting among a large number of substitute suppliers.

We first examine this economic mechanism underlying the rewiring of supply chains away

from the cap-and-trade by re-estimating our baseline regression on sub-samples defined by different levels of product market competition. Table 6 presents the baseline coefficient estimates for sub-samples characterized by a pre-treatment Herfindahl-Hirschman Index (HHI) concentration above or below the median. The HHI is calculated at the three-digit SIC code level in columns (1) and (2), and within the matched direct competitors' group of each treated supplier in columns (5) and (6). In columns (3) and (4), we focus on sub-samples of suppliers above and below the median Lerner Index—computed as the average ratio of net income over sales (at the three-digit SIC code level), capped between zero and one. Columns (7) and (8) provide estimates for suppliers exposed to a pre-treatment number of competitors in their matched direct competitors' group below or above the median. Across all these measures of competition, results are statistically significant and economically meaningful for suppliers operating in more competitive industries across all measures of competition. Thus, the effects are more pronounced in less concentrated industries, industries with a lower Lerner Index, and industries with more competitors.

Similarly, switching costs may influence the restructuring of supply chains. Industries producing standardized inputs, which allows for easier substitution, are more likely to see the termination of business relationships when faced with increased transition risks (Barrot and Sauvagnat, 2016). Additionally, this effect is expected to be concentrated among customer-supplier pairs with weaker ties, where customers are less likely to be locked in their existing relationships with suppliers.

To assess the role of switching costs in the rewiring of supply chains away from the cap-and-trade, we estimate equation (1) but split the sample based on the presence of high and low switching costs. In Panel A of Table 7, we categorize the sample according to supplier characteristics: specialized versus standardized goods, based on the two-digit SIC code classification proposed by Giannetti, Burkart, and Ellingsen, 2011, and above-median versus below-median R&D stock-to-assets ratio. In Panel B, we further segment the sample based

on the strength of the ties between the customer and supplier as proxied by the geographic proximity of customers and suppliers (customers in the United States vs. customers abroad) and the duration of the relationships (below vs. above median duration).

Consistent with the proposed economic mechanism, Panel A of Table 7 shows that the increased likelihood of treated suppliers experiencing the termination of customer relationships is concentrated among suppliers that produce standardized inputs and those with a below-median investment in innovation as proxied by R&D stock.[11] Establishing and maintaining customized supplier-customer relationships is costly, indicating that firms face important decisions regarding whether to establish or terminate these relationships. Panel B results indicate that the impact of the cap-and-trade program is more pronounced when switching costs are lower, as indicated by shorter relationship duration (columns (3) and (4)). We do not find significant differences between customers in the United States vs customers abroad, suggesting that switching costs related to the nature of the supplied good and the relationship duration are more important considerations.

5.2 Real effects

Next, we refine our analysis of the economic mechanisms underlying our results by examining the financial performance of affected suppliers. As indicated by anecdotal evidence from affected suppliers' SEC filings reported in Table IA1 of the Internet Appendix, the introduction of the California cap-and-trade program appears to place these suppliers at a competitive disadvantage.

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

$$Y_{i,t+1} = \beta_1 Treated_i \times Post_t + \beta_2 Specialized_i \times Treated_i \times Post_t + \mu_i + \mu_{s(i),t} + \epsilon_{i,t}, \quad (3)$$

[11] Notably, approximately 86% unique customers in our sample have at least one standardized supplier.

where $Y_{i,t+1}$ is the supplier's output (logarithm of revenues), cost of sales (COGS-to-lagged total assets ratio), size (logarithm of total assets), change in tangible assets (change in PPE-to-lagged total assets ratio) and profitability (ROA). $Specialized_i$ is a dummy variable that takes the value of one for suppliers producing specialized inputs (Giannetti et al., 2011). The regressions include supplier fixed effects (μ_i) and supplier sector-by-year ($\mu_{s(i),t}$) fixed effects.

To match treated suppliers with non-treated counterparts, we use an exact match based on location (U.S. firms), industry, and apply a propensity score weighting approach using firm size and profitability. We employ the nearest neighbor algorithm to ensure that each treated supplier is matched with at least one control supplier.[12]

Table 8 presents the results. Column (1), shows that affected suppliers' revenues are relatively lower by 11% after the introduction of the California cap-and-trade program. Furthermore, column (2) shows that the reduction in revenues is about 15% and statistically significant among suppliers producing standardized inputs. Columns (3) and (4) indicate that the average cost of sales for affected suppliers increases following the introduction of cap-and-trade, with a significant impact of about 5 percentage points among those producing standardized inputs. Although our measure does not directly capture suppliers' marginal costs, the observed increase in average COGS aligns with the anticipated rise in costs due to the cap-and-trade program (e.g., costs associated with emission permits, monitoring and reporting greenhouse gas (GHG) emissions, and higher prices for other raw inputs). Columns (5) and (6) show that treated suppliers experience a significant differential reduction in assets relative to control suppliers of 19% after the policy's implementation, driven primarily by those producing standardized inputs with a differential reduction of 35%.

Columns (7) and (8) show that suppliers of standardized inputs reduce investment (measured as the change in tangible assets PPE divided by total assets) by 2.5 percentage points. Additionally, columns (9) and (10) indicate a decline in profitability (ROA) for affected sup-

[12]For each supplier, the maximum weight determined by the algorithm during the pre-treatment period is applied consistently to all observations of that supplier throughout the sample.

pliers. This effect is particularly evident among suppliers of standardized inputs, who see a reduction in profitability of 6 percentage points. Overall, these findings confirm that the California cap-and-trade program negatively affected treated suppliers, especially when their customers face relatively low switching costs to alternative options. In contrast, suppliers of specialized inputs appear more capable of passing on some of the cap-and-trade costs to their customers, which helps explain the observed differential effects between treated and control suppliers.

We conclude our examination of the economic mechanisms underlying the rewiring of supply chains in reaction to the introduction of the cap-and-trade by investigating whether the transition risk shock propagates through the production network to customers indirectly exposed to the program. If customers can promptly and effectively terminate their relationships with suppliers subject to the program, they should be shielded from the event's propagation. Furthermore, we do not anticipate that customers will incur significant financial losses when switching to a different supplier after the program's introduction, as we observe that the termination of supplier relationships predominantly occurs when switching costs are relatively low.

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

$$Y_{j,t+1} = \beta Has\ Treated\ Supplier_j \times Post_t + \eta_j + \mu_{s(j),t} + \epsilon_{j,t}, \tag{4}$$

where $Y_{j,t+1}$ is the customer's output (logarithm of revenues), the average cost of sales (COGS-to-assets ratio), size (logarithm of total assets), change in tangible assets (change in PPE-to-assets ratio) and profitability (ROA).

$Has\ Treated\ Supplier_j$ is a dummy variable that takes the value of one if customer j has at least one treated supplier 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 fixed effects and industry-by-year fixed effects.

Table 9 presents the results. We find that customers exposed to treated suppliers do not experience a significant decline in revenues or an increase in the average cost of sales. Furthermore, these affected customers do not reduce their assets, cut investment, or see a significant deterioration in their profitability. Overall, the results indicate that customers can promptly and effectively realign their supply chain by moving away from suppliers subject to the program, especially if they face low switching costs.

5.3 Customers' climate transition risks

We have presented evidence that product market competition and switching costs prompt a restructuring of supply chains away from suppliers affected by the cap-and-trade program. In this section, we explore whether customers who exhibit greater environmental awareness or who anticipate future regulation of supply chain emissions may prefer to maintain relationships with cap-and-trade-affected suppliers to potentially benefit from reductions in their scope 3 emissions.

To test this hypothesis, we analyze sub-samples of customers divided at the pre-treatment industry-level median of climate change attention, as measured by Sautner et al. (2023).[13] Table 10 presents the estimates of the regression in equation (1) for these subsamples. Columns (1) and (2) show that supply chain restructuring is predominantly observed among customers with lower environmental awareness.

We further investigate this issue using alternative firm-level proxies for exposure to climate transition risks. In columns (3)-(6), we examine the effects within sub-samples of customers headquartered in states classified as Democrat or Republican based on the 2016 elections, as well as in states that are members of the U.S. Climate Alliance coalition (as of 2017).

[13]This measure is based on the frequency of climate change-related language in discussions between analysts and management during earnings calls defined at the firm-year level. Data is available at: Sautner, Van Lent, Vilkov, and Zhang (2020).

These measures serve as non-time-varying proxies for the sensitivity to environmental issues in these states, in particular climate transition risks. Our estimates in columns (3) and (4) confirm that supply chain restructuring is concentrated among customers headquartered in Republican states. Columns (5) and (6) also indicate that customers headquartered in states that are not part of the U.S. Climate Alliance are more likely to restructure their supply chain; however, the effect is not statistically significant.

6 Environmental effects

In this section, we explore the environmental implications of supply chain-driven carbon leakage resulting from the California cap-and-trade program.

To conduct this analysis, we construct firm- and supply chain-level emissions measures. We start by gathering each supplier's facility-level emissions data from the EPA database for all U.S. facilities. We aggregate these emissions at the supplier level to create a measure of emission intensity, defined as total emissions normalized by the firm's assets. We obtain U.S.-wide EPA emissions data for 501 suppliers listed in FactSet Revere between 2010 and 2017. We also rely on scope 1-2 emissions intensities directly reported by firms (sourced from CDP). Using our supply chain linkages data, we then compute supply chain emissions for each customer each year: the average U.S.-wide direct supply chain emission intensity. We also replicate this test using scope 3 emission intensity estimated by the ICE Climate Transition Finance team.

Our self-constructed measures have certain limitations compared to emissions data from commercial data providers. The primary drawback is that they only partially capture the total emissions produced by firms. This limitation arises because our data is based on a U.S.-wide EPA disclosure requirement, which mandates reporting only for facilities emitting at least 25,000 tons of CO2 equivalents annually. Consequently, emissions from smaller facilities and non-U.S. operations may be excluded. However, our measures have the advantage of

avoiding the known quality issues associated with inferred scope 3 emissions data (Aswani et al., 2024), which researchers often rely on due to the limited availability of comprehensive corporate scope 3 emissions reporting.[14]

We first use these data to examine the environmental impact of the California cap-and-trade program on the emissions of treated suppliers. Panel A of Table 11 focuses on the direct emissions of treated suppliers. Specifically, it presents the coefficient estimates from equation (3), where $Y_{i,t+1}$ represents various measures of emissions of treated suppliers. In column (1), the dependent variable is the supplier's U.S.-wide emission intensity that we calculate using EPA data, whereas in column (2), it is the total scope 1 and 2 emission intensity (sourced from CDP). Our estimates do not indicate that treated suppliers experience a reduction in direct emissions following the implementation of the cap-and-trade program. In contrast, they show higher U.S.-wide emission intensity. These effects are only statistically significant using the U.S.-wide emissions from the EPA. Overall, this evidence suggests that emission intensity was not significantly reduced after the introduction of the cap-and-trade.

In Panel B, we examine the supply chain emissions of customers indirectly affected by the policy through their relationships with suppliers. Specifically, we employ the specification in equation (4). In column (1), the dependent variable, $Y_{j,t+1}$, represents the average U.S.-wide emission intensity of the suppliers of each customer, serving as a proxy for the carbon footprint of a customer's direct supplier supply chain choices. In column (2), we use inferred upstream scope 3 emission intensity data from ICE Climate Transition Finance.[15]

Our findings indicate that customers who have business relationships with treated suppliers exhibit a significant deterioration in their supply chain environmental performance. This

[14]Our proxy for supply chain emissions of each customer differs from the traditional measure of customers' scope 3 emissions. Our estimate captures the total emissions footprint of each customer's first-tier suppliers. In contrast, upstream scope 3 emissions, as inferred by data providers, account for emissions produced throughout a customer's entire supply chain. Additionally, these inferred scope 3 emissions are scaled by the volume of goods and services a customer purchases from each supplier.

[15]Due to data availability limitations inherent in the horizon of our sample, we use inferred scope 3 emissions data.

evidence suggests that the cap-and-trade policy may have inadvertently prompted a shift toward more environmentally detrimental supply chains. Customers indirectly impacted by the policy—who, according to our baseline results, reconfigured their supply chains away from California—appear to have transitioned to suppliers located outside the carbon pricing jurisdiction. This shift is likely driven by the relatively lower costs associated with producing emissions or using polluting fuels in these regions, which are not subject to the same carbon pricing constraints. In Table IA5 of the Internet Appendix, we explicitly measure the differential carbon footprint of supply chains that in a given year are rewired away from the cap-and-trade program, relative to "counterfactual" supply chains that remain linked to suppliers subject to the cap-and-trade. Supporting our interpretation of the cap-and-trade program being followed by a shift to more polluting supply chains, we find that, after the introduction of the policy, the average U.S.-wide emission intensity of rewired supply chains is relatively higher.

7 Conclusion

Over the past decades, many countries have implemented environmental policies to regulate firms' carbon emissions. However, many of these initiatives have not been coordinated across different regions and countries. In this paper, we present evidence that the rewiring of supply chains is a mechanism through which firms contribute to the practice of carbon leakage.

Using a difference-in-differences methodology, we find that suppliers subject to the California cap-and-trade policy are significantly more likely to experience the termination of pre-existing customer relationships. Additionally, suppliers exposed to the policy are less likely to establish new customer relationships post-policy implementation. These findings suggest a substantial rewiring of supply chain networks away from participants in the cap-and-trade program.

Our results are most pronounced among suppliers operating in more competitive markets,

those producing standardized inputs or investing less in innovation, and those maintaining weaker ties with their customers. These suppliers face a competitive disadvantage following the introduction of the cap-and-trade program, leading to a deterioration in their financial performance, particularly if they produce standardized inputs. Moreover, these effects are concentrated among customers headquartered in states with relatively weaker environmental awareness, where the likelihood of future carbon pricing is lower.

We also examine the environmental implications of carbon pricing policies. Our analysis shows that suppliers affected by the cap-and-trade program do not report improvements in direct emission intensity; if anything, there is an increase in emissions. Furthermore, we observe a worsening of the supply chain carbon footprint among customers indirectly affected through their supply chains. Taken together, these findings highlight potential side effects of carbon pricing policies that may, at least partially, counteract their intended positive environmental impact.

Our paper has significant policy implications and contributes to the ongoing discussion on the necessity for coordinated climate action. Our findings suggest that harmonizing climate policies across jurisdictions and regulating upstream supply chain emissions could create more equitable market conditions for firms operating in regions or countries with different climate policies.

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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	360,735
Starting	0.32	0.47	0.00	0.00	1.00	360,735
Relationship duration (years)	3.16	2.61	2.00	1.00	15.00	360,735
Supplier treated	0.03	0.17	0.00	0.00	1.00	360,735
Supplier total assets (billion $)	29.28	77.99	2.61	0.01	531.86	360,065
Supplier ROA	0.07	0.16	0.10	-0.80	0.34	343,907
Supplier leverage	0.25	0.21	0.22	0.00	0.99	358,139
Supplier Tobin Q	1.97	1.37	1.54	0.61	8.81	325,823
Supplier R&D stock	0.39	0.75	0.10	0.00	5.50	360,735
Customer total assets (billion $)	67.83	145.35	14.23	0.02	1,027.62	132,340
Supplier CA emission intensity std.	0.05	1.00	0.00	0.00	34.86	360,735
Sales (million $)	252.21	752.16	26.89	0.11	5,492.37	18,539
Panel B: Supplier-Year Data						
Supplier treated	0.01	0.12	0.00	0.00	1.00	36,588
Total assets (billion $)	11.60	40.06	0.85	0.00	308.85	36,118
Revenues (billion $)	4.97	13.90	0.54	0.00	95.21	36,055
Net income/Assets	-0.09	0.46	0.02	-3.19	0.49	28,808
ROA	0.01	0.38	0.09	-2.33	0.53	30,430
COGS/Assets	0.61	0.68	0.40	0.00	3.81	30,488
ΔPPE/Assets	0.02	0.11	0.00	-0.24	0.67	30,273
Number of customers	13.64	21.30	6.00	1.00	534.00	25,407
U.S.-wide emission intensity	407.60	853.88	78.96	0.00	5,600.23	2,889
Scope 1-2 emission intensity	319.61	903.90	34.87	0.54	5,945.01	2,994
Panel C: Customer-Year Data						
Has treated supplier	0.18	0.38	0.00	0.00	1.00	29,492
Rewired from treated supplier	0.10	0.30	0.00	0.00	1.00	2,759
Customer treated	0.01	0.11	0.00	0.00	1.00	29,492
Total assets (billion $)	11.51	39.29	1.11	0.00	307.29	29,131
Revenues (billion $)	4.78	12.99	0.63	0.00	88.63	29,062
Net income/Assets	-0.08	0.42	0.02	-2.87	0.44	22,695
ROA	0.01	0.36	0.09	-2.18	0.51	24,629
COGS/Assets	0.59	0.67	0.38	0.00	3.71	24,660
ΔPPE/Asset	0.02	0.10	0.00	-0.21	0.61	24,507
Mean supplier U.S.-wide emission intensity	148.86	300.82	29.38	0.00	1,796.33	7,295
Goods and services scope 3 emission intensity	66.90	110.24	26.79	0.04	713.47	4,176

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 A1 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	Difference
Supplier total assets (log)	7.752	11.269	-3.517***
	(0.004)	(0.015)	(0.024)
Supplier ROA	0.072	0.107	-0.035***
	(0.000)	(0.001)	(0.002)
Supplier leverage	0.249	0.337	-0.088***
	(0.000)	(0.002)	(0.002)
Supplier Tobin Q	1.983	1.525	0.458***
	(0.002)	(0.006)	(0.014)
Supplier R&D stock	0.394	0.092	0.302***
	(0.001)	(0.001)	(0.007)

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	0.20	0.40	0.00	0.00	1.00	112,677
Starting	0.29	0.45	0.00	0.00	1.00	112,677
Relationship duration (years)	3.46	2.79	2.00	1.00	15.00	112,677
Supplier treated	0.09	0.28	0.00	0.00	1.00	112,677
Supplier total assets (billion $)	33.80	90.19	2.62	0.01	531.86	112,324
Supplier ROA	0.07	0.18	0.11	-0.80	0.34	112,206
Supplier Tobin Q	1.95	1.30	1.58	0.61	8.81	105,055
Supplier leverage	0.25	0.20	0.23	0.00	0.99	111,836
Supplier R&D stock	0.51	0.94	0.17	0.00	5.50	112,677
Customer total assets (billion $)	62.06	118.79	15.51	0.01	1,027.62	43,879

This table contains summary statistics for the main variables of interest computed on the matched sample. The matching approach is described in Section 3.1. The sample period is from 2010 to 2017. All continuous variables are winsorized at the 1 and 99% level. Refer to Table A1 in Appendix for variable definitions.

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

	(1)	(2)	(3)	(4)	(5)
Treated × Post	0.082*	0.061***	0.051**	0.047**	0.023**
	(0.046)	(0.021)	(0.021)	(0.021)	(0.009)
Supplier total assets (log)			0.010	0.012	0.100***
			(0.019)	(0.020)	(0.025)
Supplier ROA			-0.078	-0.109*	-0.003
			(0.058)	(0.060)	(0.048)
Supplier leverage			-0.107	-0.133	-0.216***
			(0.075)	(0.081)	(0.062)
Supplier Tobin Q			0.015	0.016	0.007
			(0.014)	(0.015)	(0.008)
Supplier R&D stock			-0.036*	-0.037*	0.048***
			(0.020)	(0.021)	(0.012)
Relationship duration			0.003	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	
Year FE	Yes				
Supplier FE	Yes	Yes	Yes	Yes	
Customer FE	Yes				
Customer × Year FE		Yes	Yes	Yes	
Supplier × Competitor group FE					Yes
Customer × Year × Competitor group FE					Yes
Obs.	110,048	83,129	76,220	71,140	112,370
R^2	0.317	0.832	0.839	0.844	0.833

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 3.1. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25,000 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-by-competitor group and competitor group in column (5) are reported in parentheses. Refer to Table A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 5: Probability of Starting New Relationship and Cap-and-Trade Program

	(1)	(2)	(3)	(4)	(5)
Treated × Post	-0.354***	-0.082***	-0.084***	-0.099***	-0.025
	(0.114)	(0.022)	(0.023)	(0.022)	(0.022)
Supplier total assets (log)			-0.015	-0.023	0.037**
			(0.022)	(0.024)	(0.015)
Supplier ROA			0.110*	0.108**	-0.041
			(0.057)	(0.053)	(0.060)
Supplier leverage			0.034	0.020	0.166***
			(0.044)	(0.048)	(0.049)
Supplier Tobin Q			0.015***	0.012**	0.011
			(0.005)	(0.005)	(0.009)
Supplier R&D stock			0.018	0.015	0.040**
			(0.015)	(0.016)	(0.017)
Matched supplier	Yes	Yes	Yes	Yes	
Matched supplier competitor group					Yes
Excl. treated customers				Yes	
Year FE	Yes				
Supplier FE	Yes	Yes	Yes	Yes	
Customer FE	Yes				
Customer × Year FE		Yes	Yes	Yes	
Supplier × Competitor group FE					Yes
Customer × Year × Competitor group FE					Yes
Obs.	110,048	83,129	76,220	71,140	112,370
R^2	0.395	0.857	0.860	0.866	0.865

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 3.1. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25,000 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-by-competitor group and competitor group in column (5) are reported in parentheses. Refer to Table A1 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: 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	High	Low
Treated × Post	0.008	0.095***	0.017	0.091***	0.010	0.037***	0.035**	0.014
	(0.021)	(0.032)	(0.023)	(0.035)	(0.012)	(0.010)	(0.014)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes				
Matched supplier competitor group					Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes				
Customer × Year FE	Yes	Yes	Yes	Yes				
Supplier × Competitor group FE					Yes	Yes	Yes	Yes
Customer × Year × Competitor group FE					Yes	Yes	Yes	Yes
Obs.	43,102	26,360	48,152	21,976	48,079	64,291	59,932	52,438
R^2	0.873	0.835	0.861	0.745	0.845	0.821	0.837	0.826

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 3.1. 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-by-competitor group and competitor group level in columns (5) to (8) are reported in parentheses. Refer to Table A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 7: Probability of Termination and Cap-and-Trade Program: Input Specificity

Panel A				
	(1)	(2)	(3)	(4)
	Input type		R&D stock	
	Specialized	Standardized	High	Low
Treated × Post	-0.003	0.065**	0.026	0.070**
	(0.017)	(0.032)	(0.028)	(0.029)
Controls	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes
Obs.	41,947	21,002	38,537	31,395
R^2	0.893	0.828	0.840	0.857
Panel B				
	(1)	(2)	(3)	(4)
	Customer HQ		Relationship duration	
	US	Abroad	High	Low
Treated × Post	0.044**	0.048*	-0.036	0.052*
	(0.019)	(0.027)	(0.025)	(0.027)
Controls	Yes	Yes	Yes	Yes
Matched supplier	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes
Obs.	41,173	32,045	19,729	50,853
R^2	0.791	0.878	0.859	0.869

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 3.1. 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 A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 8: Supplier's Real Effects of Cap-and-Trade Program

	Panel A					
	(1)	(2)	(3)	(4)	(5)	(6)
	Revenues (log)	Revenues (log)	COGS/Assets	COGS/Assets	Total assets (log)	Total assets (log)
Treated × Post	-0.108**	-0.146**	0.003	0.047**	-0.193***	-0.354***
	(0.045)	(0.061)	(0.016)	(0.020)	(0.052)	(0.060)
Specialized × Treated × Post		-0.059		-0.087***		0.238***
		(0.071)		(0.026)		(0.070)
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.	10,442	8,747	10,815	9,081	10,869	9,121
R^2	0.980	0.983	0.869	0.871	0.984	0.986
	Panel B					
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ PPE/Assets	Δ PPE/Assets	ROA	ROA	Net income/Assets	Net income/Assets
Treated × Post	-0.025**	-0.024*	-0.048***	-0.062***	-0.071***	-0.111***
	(0.012)	(0.013)	(0.011)	(0.015)	(0.016)	(0.021)
Specialized × Treated × Post		0.019		0.044**		0.106***
		(0.013)		(0.017)		(0.023)
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.	10,811	9,084	10,803	9,071	10,608	9,067
R^2	0.452	0.418	0.797	0.807	0.703	0.715

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 logarithm of revenues; in columns (3) and (4), it is the ratio of COGS over lag of total assets; in columns (5) and (6), it is the logarithm of total assets; in Panel B columns (1) and (2), it is the yearly change in PPE 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 net income over lag of total assets. 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 A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 9: Customer's Real Effects of Cap-and-Trade Program

	(1) Revenues (log)	(2) COGS/Assets	(3) Total assets (log)	(4) Δ PPE/Assets	(5) ROA	(6) Net income/Assets
Has treated supplier × Post	0.009	-0.018	0.014	-0.004	-0.008	-0.006
	(0.034)	(0.017)	(0.033)	(0.004)	(0.017)	(0.014)
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.	19,041	19,564	19,688	19,390	18,114	19,524
R^2	0.975	0.901	0.980	0.442	0.698	0.795

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 logarithm of revenues; in column (2) it is the ratio of COGS over lag of total assets; in column (3) it is the logarithm of assets; in column (4) it is the yearly change in PPE over lag of total assets; in column (5) it is EBITDA over lag of total assets; in column (6) it is the ratio of net income over the lag of total assets. 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 25,000 tonnes of CO2 equivalents. Robust standard errors clustered at the customer level are indicated in parentheses. Refer to Table A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table 10: 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	-0.007	0.066**	-0.025	0.074*	-0.004	0.060
	(0.019)	(0.026)	(0.027)	(0.039)	(0.027)	(0.045)
Supplier total assets (log)	0.033	0.002	-0.010	-0.023	-0.006	-0.015
	(0.025)	(0.028)	(0.034)	(0.029)	(0.036)	(0.027)
Supplier ROA	-0.151**	0.026	0.012	0.002	0.081	0.002
	(0.061)	(0.086)	(0.098)	(0.093)	(0.107)	(0.088)
Supplier leverage	-0.027	-0.113	0.124*	-0.044	0.165**	-0.044
	(0.064)	(0.103)	(0.069)	(0.071)	(0.075)	(0.070)
Supplier Tobin Q	-0.012	0.005	-0.003	0.004	-0.004	0.002
	(0.009)	(0.009)	(0.009)	(0.012)	(0.010)	(0.010)
Supplier R&D stock	-0.023	-0.012	-0.004	-0.043*	0.009	-0.020
	(0.017)	(0.022)	(0.024)	(0.024)	(0.025)	(0.022)
Relationship duration	0.001	0.000	0.000	0.005**	0.003	0.003
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Matched supplier	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17,064	15,033	8,170	11,546	8,039	11,649
R^2	0.831	0.816	0.853	0.802	0.861	0.789

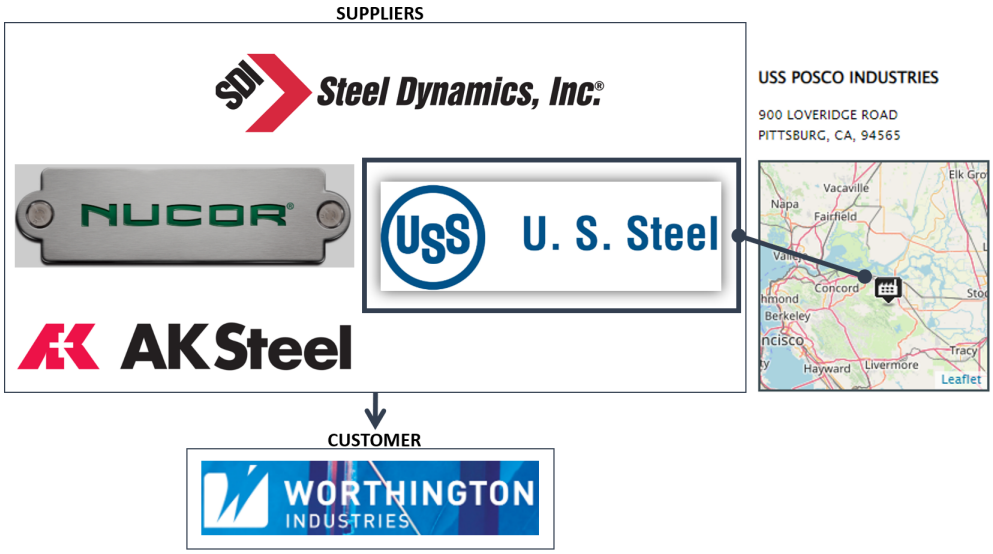
The table contains the regression results for the baseline specification, reported in Equation 1. The dependent variable takes the value 1 if the supplier-customer relationship ends in a given year and 0 in the previous years of the relationship. The regression is estimated on matched sub-samples supplier-customer pair-year panel from 2010 to 2017. The matching approach is described in Section 3.1. 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 A1 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 11: Environmental Effects of Cap-and-Trade Program

Panel A: Scope 1-2 Emissions		
	(1)	(2)
	U.S. emission intensity	Scope 1-2 emission intensity
Treated × Post	126.557**	84.917
	(59.751)	(67.118)
Matched supplier	Yes	Yes
Supplier FE	Yes	Yes
Supplier sector × Year FE	Yes	Yes
Obs.	2,186	900
R^2	0.953	0.982
Panel B: Supply Chain Emissions		
	(1)	(2)
	Average U.S. emission intensity	Scope 3 emission intensity
Has treated supplier × Post	43.973***	29.073***
	(13.985)	(11.205)
Matched customer	Yes	Yes
Customer FE	Yes	Yes
Customer sector × Year FE	Yes	Yes
Obs.	5,200	2,626
R^2	0.919	0.738

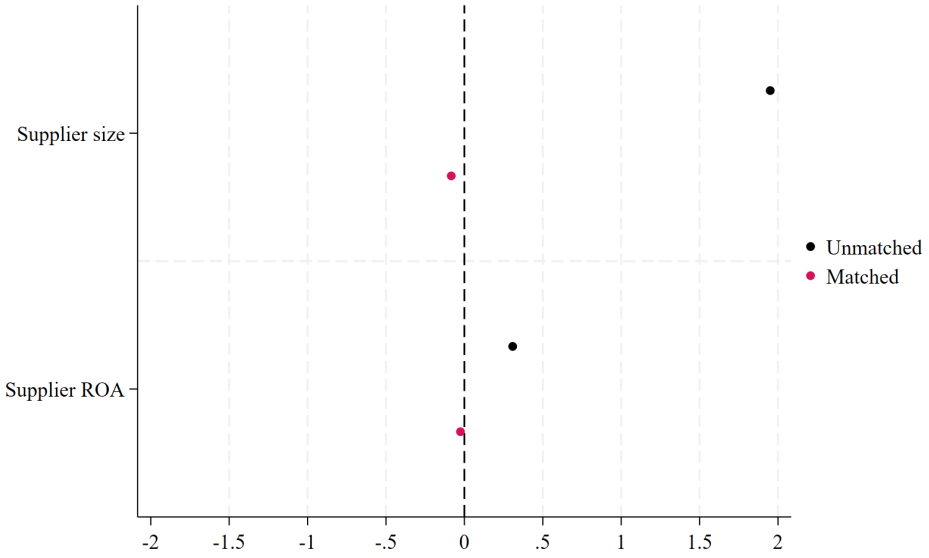
In Panel A, the table shows the regression results for the specification reported in Equation 3. The regression is estimated on a matched supplier-year panel from 2010 to 2017. The matching approach is described in Section 5.1. The dependent variable in column (1) is a firm's U.S.-wide emissions intensity computed as the firm's total U.S.-wide emissions (obtained by grouping EPA facility-level emissions at the firm parent level) divided by its total assets. The dependent variable in column (2) is a firm's 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 average U.S.-wide emission intensity of each customer's supplier (in other words, we compute the average U.S.-wide emission divided by the total assets of the direct suppliers of a given customer). In column (2), 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. 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 A1 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



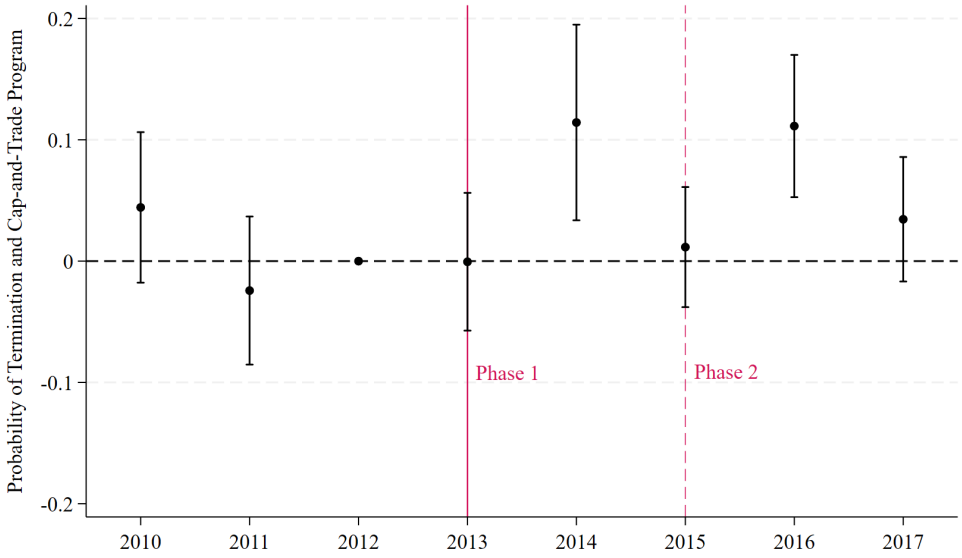
This figure illustrates the structure of the dataset through the example of the treated supplier U.S. Steel and its customer Worthington Industries. According to the EPA FLIGHT data, the U.S. Steel POSCO facility mapped close to San Francisco on the right-hand side of the figure produced sufficient emissions 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: Probability of Termination around Cap-and-Trade Program



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 25,000 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.

Appendix

Table A1: 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).

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Variable Name	Description and Source
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).
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).

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Variable Name	Description and Source
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).
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).
Sales	Sales between a customer and supplier in a given year (Customer-Supplier-Year level, Compustat Segments).

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.

Internet Appendix for

Rewiring Supply Chains Through Climate Policy

Table IA1: 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

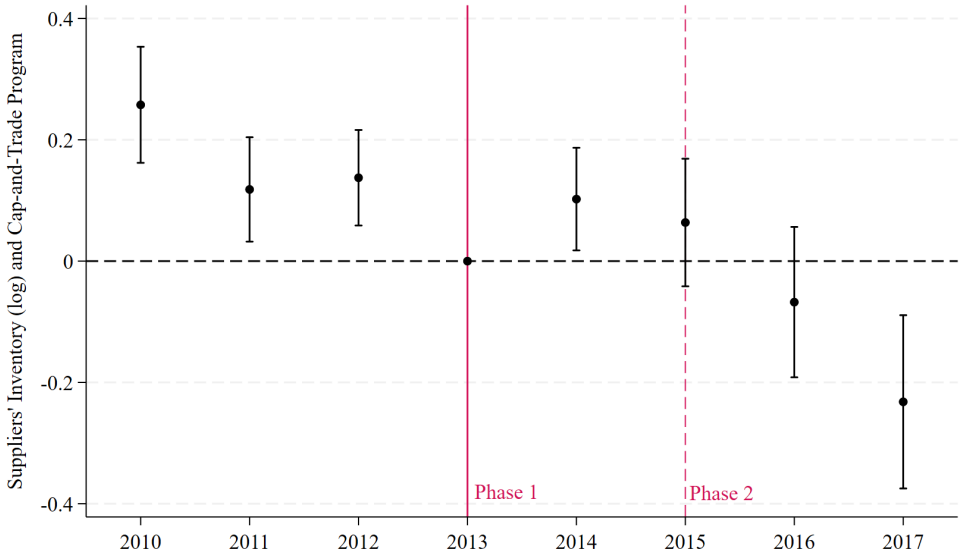
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Treated supplier	SEC filings excerpts
Valero Energy Corporation	"Governmental restrictions on greenhouse gas emissions – including so-called "cap-and-trade" programs targeted at reducing carbon dioxide emissions – could result in material increased 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

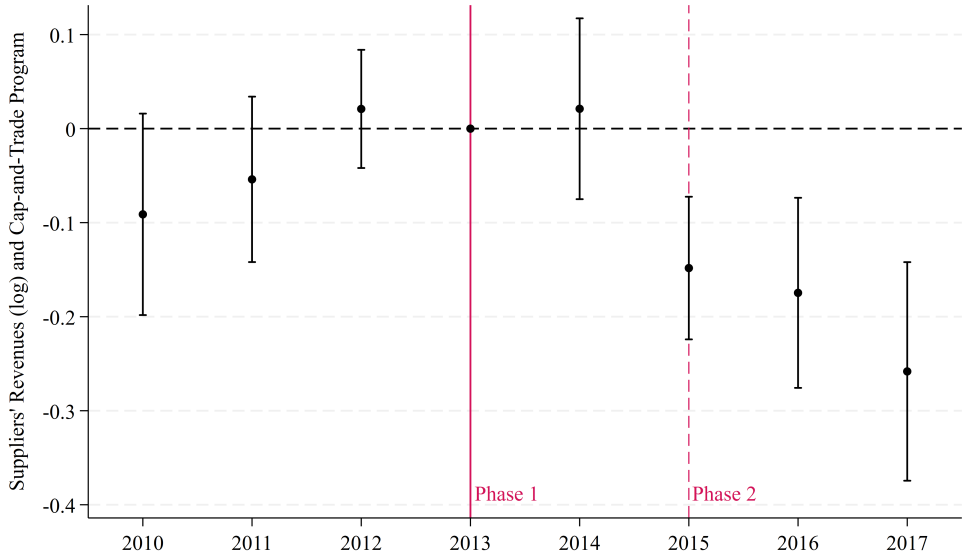
The table shows excerpts of the SEC filings of a sub-sample of treated suppliers. The excerpts provide anecdotal evidence of the impacts of the California cap-and-trade policy on suppliers' financial performance and economic activity.

Figure IA1: Difference in Suppliers' Inventory around Cap-and-Trade Program



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' inventories (log). 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 25,000 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.

Figure IA2: Difference in Suppliers' Revenues around Cap-and-Trade Program



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' revenues (log). 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 25,000 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.

Table IA2: Probability of Termination and Cap-and-Trade Program: Treatment Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Intensity of treatment × Post	0.012***	0.009**	0.012***	0.012**	0.003*	0.011**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)	(0.005)
Treated × Post						0.022
						(0.023)
Supplier total assets (log)			0.010	0.012	0.097***	0.011
			(0.018)	(0.020)	(0.025)	(0.018)
Supplier ROA			-0.074	-0.103*	-0.005	-0.075
			(0.054)	(0.057)	(0.048)	(0.054)
Supplier leverage			-0.086	-0.110	-0.218***	-0.089
			(0.065)	(0.070)	(0.062)	(0.065)
Supplier Tobin Q			0.010	0.011	0.006	0.011
			(0.011)	(0.012)	(0.008)	(0.012)
Supplier R&D stock			-0.033**	-0.034*	0.046***	-0.032*
			(0.017)	(0.018)	(0.012)	(0.017)
Relationship duration			0.002	0.003	0.002	0.003
			(0.002)	(0.003)	(0.001)	(0.002)
Matched supplier	Yes	Yes	Yes	Yes		Yes
Matched supplier competitor group					Yes	
Excl. treated customers				Yes		
Year FE	Yes					
Supplier FE	Yes	Yes	Yes	Yes		Yes
Customer FE	Yes	Yes	Yes	Yes		Yes
Customer × Year FE		Yes	Yes	Yes		Yes
Supplier × Competitor group FE					Yes	
Customer × Year × Competitor group FE					Yes	
Obs.	110,048	83,129	76,220	71,140	112,370	76,220
R^2	0.320	0.833	0.840	0.845	0.833	0.840

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 3.1. To code the matching approach, we rely on the *kmatch Stata module*, Jann (2017). In column (4), customers that produce emissions above 25,000 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-by-competitor group and competitor group in column (5) are reported in parentheses. Refer to Table A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table IA3: 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	(8) Alt. FE	(9) Sales (log)
Treated × Post	0.051***		0.049*	0.055**	0.387***			0.033**	-0.210*
	(0.013)		(0.025)	(0.028)	(0.097)			(0.015)	(0.113)
Treated 2012 × Post		0.025*							
		(0.014)							
HQ CA × Post						0.002			
						(0.018)			
US Climate Alliance × Post							-0.022		
							(0.042)		
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Matched supplier	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Matched sample					Yes				
Supplier FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier sector FE					Yes				
Supplier sector × Year FE								Yes	
Obs.	76,220	70,903	69,327	49,647	48,862	84,554	5,880	76,218	4,457
R^2	0.839	0.889	0.760	0.868		0.508	0.770	0.848	0.973

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 3.1. In column (7), the placebo treatment group consists of control suppliers that in 2010 produce emissions above 25,000 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 3.1. In column (8), the baseline specification is further saturated with the use of supplier sector-by-year fixed effects. In column (9), the baseline specification is reproduced over a Compustat Segment sample of supplier-customer pairs. The dependent variable is the logarithm of the sales between the pair in a given year. Treated suppliers are matched to further control observations according to the matching approach described in Section 3.1. 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 A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table IA4: 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**	0.072***	0.074***	0.034**	0.043***
	(0.014)	(0.022)	(0.023)	(0.016)	(0.015)
Supplier size	0.022**	0.024	0.049**	0.036**	0.070***
	(0.010)	(0.017)	(0.020)	(0.017)	(0.023)
Supplier profitability	-0.030	-0.096**	-0.060	-0.027	-0.084
	(0.030)	(0.042)	(0.045)	(0.046)	(0.053)
Supplier debt	-0.028	-0.078	-0.110**	-0.029	-0.093*
	(0.027)	(0.052)	(0.051)	(0.041)	(0.049)
Supplier Tobin Q	-0.004	0.002	0.005	-0.001	0.004
	(0.004)	(0.007)	(0.007)	(0.004)	(0.005)
Supplier R&D stock	0.001	-0.015	-0.001	-0.002	0.004
	(0.008)	(0.011)	(0.012)	(0.010)	(0.012)
Supplier cash			0.041		
			(0.065)		
Relationship length	0.006***	0.004***	0.004***	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Alternative matching		Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes
Obs.	248,709	76,220	72,222	50,606	50,497
R^2	0.373	0.844	0.832	0.414	0.582

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 A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.

Table IA5: Environmental Effects of Cap-and-Trade Program on Supply Chains

	(1) Average U.S. supply chain emission intensity	(2) Scope 3 emission intensity
Rewired supply chain	-139.952**	18.505*
	(61.071)	(9.708)
Rewired supply chain × Post	133.616**	-0.002
	(66.988)	(7.836)
Customers linked to treated suppliers	Yes	Yes
Customer FE	Yes	Yes
Customer sector × Year FE	Yes	Yes
Obs.	2,323	647
R^2	0.853	0.780

The table shows the regression results for the following specification:

$$Y_{i,t} = \beta_1 Rewired_{i,t} \times Post_t + \beta_2 Rewired_{i,t} + \eta_i + \mu_{s(i),t} + \epsilon_{i,t}.$$

Where $Y_{i,t}$ is either the average U.S. supply chain emission intensity, in column (1), or the inferred scope 3 emission intensity of a given customer i in year t, in column (2). $Rewired_{i,t}$ is a dummy equal to 1 if in year t, customer c sources its inputs from a supply chain that is rewired away from the cap-and-trade, i.e., if in year t, customer i has less treated suppliers than in year $t-1$, 0 otherwise. The regression is estimated on a sub-sample of customers that either continue or terminate a relationship with at least one treated supplier in a given year. The sample excludes customers directly affected by the California cap-and-trade. Standard errors are indicated in parentheses, they are clustered at the customer level. Refer to Table A1 in Appendix for variable definitions. * corresponds to $p<.10$, ** to $p<0.05$ and *** to $p<0.01$.