Rewiring Supply Chains Through Uncoordinated Climate Policy*

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December 16, 2024

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 compared to their peers unaffected by the program. The effects are more pronounced among suppliers facing high competitive pressure and producing standardized inputs. Additionally, affected suppliers experience declines in revenues, assets, and profitability. This supply chain rewiring induced by uncoordinated climate policies is consistent with carbon leakage, as customers exposed to the program through production networks show an increase in their supply chain emission intensity.

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

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*We thank Vicente Bermejo, Hans Degryse, Ulrich Hege, Thea Kolasa, Annette Krauss, Ernst Maug, Lakshmi Naaraayanan, Steven Ongena, Alex Osberghaus, Zacharias Sautner, Daniel Streitz, Lea Tschan, Felix von Meyerinck, Alexander Wagner, conference participants at the Banca d'Italia-EABCN-EUI-CEPR Joint Conference on 'The macroeconomic and financial dimensions of the green transition", ESADE, ECB, EBRD, EBA, CEPR, CompNet & IWH Conference on Finance and Productivity (FINPRO), Oklahoma University and Review of Financial Studies Climate & Energy Conference 2024, Rising Scholars Conference on Sustainable Finance, and SFI Research Days, and seminar participants at CUNEF, ESSEC, Norges Bank, the University of Groningen, and the University of Zurich for helpful comments. The authors gratefully acknowledge financial support from the Georg und Bertha Schwyzer-Winiker-Stiftung, SNSF Grant Nr. 100018 204561 / 1 (project corporate short-termism), and Fundação para a Ciência e Tecnologia (Grant PTDC/EGE-OGE/4714/2021). This paper should not be reported as representing the views of Norges Bank. The views expressed are those of the authors and do not necessarily reflect those of Norges Bank.

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1 Introduction

In recent decades, many governments have adopted climate policies to curb emissions, resulting in a patchwork of regulations across different legal jurisdictions. These uncoordinated climate policies can lead to different forms of environmental regulatory arbitrage (known as "carbon leakage"). Previous research finds that companies react to uncoordinated climate policies by moving production and emissions from facilities in jurisdictions with climate policies to facilities with unregulated emissions (Ben-David, Jang, Kleimeier, and Viehs, 2021; Bartram, Hou, and Kim, 2022). However, an equally significant form of carbon leakage could result from changes in the supply chain. Specifically, customers can shift their input source from suppliers subject to climate policies to unregulated suppliers in a strategy aimed at mitigating indirect exposure to climate transition risks and reducing supply chain uncertainty (Cosbey, Droege, Fischer, and Munnings, 2019). In turn, this can affect business relationships, trade patterns, and emissions production along supply chains.

It is ex-ante unclear whether uncoordinated climate policies lead to the rewiring of supply chains away from regulated suppliers. On the one hand, climate policies expose affected firms to climate transition risks, resulting in higher costs and reductions in jobs, capital, and output (Greenstone, 2002; Ryan, 2012), thereby placing them at a disadvantage relative to their competitors.[1] In turn, increased exposure to climate transition risks can increase risks of supply chain disruptions and trigger termination of business relationships with affected suppliers.[2] On the other hand, regulators often mitigate the impact of climate policies on firm competitiveness by granting exemptions to highly energy-intensive and trade-exposed

[1]For instance, in its Securities and Exchange Commission (SEC) 10K filings, Air Products, and Chemicals Inc. notes that "Any legislation that limits or taxes greenhouse gas (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).

[2]For instance, in its SEC 10K filings, Campbell Soup Company 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).

sectors (Fowlie, Reguant, and Ryan, 2016). Other factors may also impact the stability of supply chain relationships. High switching costs, such as those related to search efforts or input specificity (Barrot and Sauvagnat, 2016; Bernard, Moxnes, and Saito, 2019) generally increase the stickiness of supply chains. Furthermore, the anticipation of future supply chain emissions regulations (Ramadorai and Zeni, 2024), as well as pressure from environmentally conscious stakeholders and consumers (Krueger, Sautner, and Starks, 2020; Aghion, Bénabou, Martin, and Roulet, 2023) may discourage cutting down relationships with suppliers subject to climate policies.

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

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 price on emissions for firms that produce more than 25,000 tons of carbon dioxide equivalents in their California facilities. California provides an ideal setting to examine the effects of carbon pricing programs on supply chains, as no other U.S. state regulates 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 engaging in new relationships with similar suppliers not subject to the program.

We implement our identification strategy using a difference-in-differences (DiD) methodology combined with a matching approach to analyze changes in the likelihood of terminating an existing relationship with a supplier affected by the cap-and-trade program. 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. Treated suppliers are defined as firms with at least one facility in California that reported emissions exceeding 25,000 tons of CO2 equivalents in 2010. 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-year 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 2.3 to 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 an increase in the probability of ending a relationship with suppliers subject to the program between 5.8% and 12.8% of its standard deviation.

We further find that following the introduction of the carbon pricing program, the likelihood of initiating a new relationship with a supplier subject to the cap-and-trade is lower compared to control suppliers. These findings indicate a restructuring of the entire supply chain to mitigate exposure to increasing climate transition risks. In particular, the results do not support alternative explanations of the baseline findings, such as a mere reshuffling of the customer base among suppliers affected by the policy.

The higher probability of terminating relationships with suppliers subject to the cap-and-trade program might be a direct consequence of suppliers' reallocation of production outside California. For example, Bartram et al. (2022) show that financially constrained suppliers often shift their operations to plants in other states, potentially leading to the formation of new customer relationships closer to these non-Californian locations. However, we show that our baseline results remain both economically and statistically significant within the sub-sample of suppliers that operate exclusively in California, as well as among financially unconstrained suppliers. This finding indicates that heterogeneous carbon policies can create an additional channel for carbon leakage by requiring supply chain reconfigurations to avoid higher carbon costs.

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 competitive industries. In fact, customers can more effectively mitigate climate transition risk in their supply chains by switching to alternative suppliers in competitive industries. Consistent with this notion, we find that our baseline effects are more pronounced among suppliers operating in industries with a low Herfindahl-Hirschman Index (HHI), a low Lerner Index, and less concentrated groups of direct competitors.

Similarly, we expect customers facing low switching costs to source their inputs more readily and cheaply from alternative suppliers. Consistent with this prediction, we find that our baseline effects are concentrated among suppliers offering standardized inputs and those with lower investment in innovation (i.e., research and development, R&D, expenditures). The results are also stronger among suppliers with shorter relationship durations.

To further investigate the economic mechanism underlying our results, we provide firm-level evidence suggesting that the uncoordinated climate action in the U.S. impairs the competitiveness of suppliers subject to the cap-and-trade program relative to their peers, due to their different exposure to climate transition risks.[3] We find that treated suppliers experience greater declines in revenues, assets and profitability, along with a greater increase in

[3]For instance, in its SEC 10K filings, the United States Steel Corporation explicitly addresses the heterogeneity in climate 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 lower 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).

average costs of goods sold (COGS), compared to control suppliers. Furthermore, we find that the deterioration of financial performance is more pronounced for suppliers that produce standardized inputs. These findings align with those of Greenstone (2002) and Ryan (2012), indicating that firms producing standardized inputs face a higher probability of supply chain disruption. This increased risk may prompt customers to switch suppliers to mitigate the impact of climate transition risks.

We then explore whether customers anticipate 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 uncoordinated climate policies. We find that the introduction of the cap-and-trade program does not significantly reduce the total emission intensity (scope 1 and 2 emissions relative to revenues or assets) of treated suppliers compared to those in the control group. Furthermore, consistent with carbon leakage, we observe an increase in customer emissions across their supply chains following the program's implementation. Specifically, firms that source from at least one affected supplier exhibit a higher intensity of supply chain emission (scope 3) than similar firms without such exposure. These findings highlight the unintended consequences of uncoordinated climate policies, consistent with the primary mechanisms of carbon leakage described 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; Laeven and Popov, 2023; Duchin, Gao, and Xu, 2024; Ivanov, Kruttli, and Watugala, 2024). Related to our paper, Ben-David et al. (2021) and Bartram et al. (2022) provide evidence of within-firm reallocation of production to facilities outside carbon-regulated jurisdictions.[4] Our paper builds on this literature by studying the export of goods from cap-and-trade regimes through the relationships between suppliers exposed to climate transition risks and their customers. Importantly, we document a novel carbon leakage mechanism that occurs beyond the firm's boundaries through supply chain realignment.

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, Duan, Liang, and Ng, 2021a; Dai, Liang, and Ng, 2021b; 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).

[4]In contemporary work, Coster, di Giovanni, and Mejean (2024) show that as the EU ETS tightened, French firms increased their imports of dirty products from countries outside of the EU-ETS. Martin, Muûls, and Stoerk (2024) find no evidence of significant real effects on Belgian firms with higher indirect exposure to the EU ETS through their supply chains. However, these firms appear to respond by diversifying their supplier portfolios.

Our paper also relates to research on the impact of 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. Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) show that downstream propagation explains a sizable fraction of the decline in 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 paper focuses on climate transition risks, particularly those arising from state-level climate 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 climate policy we examine produces a more permanent impact on firms' production networks.

Last, we contribute to the literature exploring how climate regulations impact firms' behavior, performance, 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 a 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. The California cap-and-trade program was introduced in January 2013 as part of this commitment. During its first phase, from 2013 to 2014, the program focused on electricity generation (including imports) and industrial facilities that emit more than 25,000 tons of equivalent carbon dioxide (CO2) 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.[5] 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 equivalent CO2 at its California facilities. The auction price for permits was $10 per ton of CO2 equivalents in 2013, averaging approximately $12.50 between 2013 and 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 in 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 low or no carbon pricing, a phenomenon known as "carbon leakage".

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

The literature has identified several channels through which carbon leakage can occur (Cosbey et al., 2019). At the supply chain level, carbon leakage can occur via a *competitiveness channel*, which has been extensively discussed in prior research (see, for example, the comprehensive review by Fowlie, Reguant, and Ryan, 2016). According to this channel, uncoordinated climate action places suppliers subject to climate policies at a disadvantage relative to competitors, as these firms are exposed to a higher degree of climate transition risks. Downstream customers reduce this exposure to supply chain uncertainty by shifting their sourcing away from suppliers exposed to climate transition risks.

We build on this literature to identify the *competitiveness channel* of carbon leakage within the context of uncoordinated climate action in the United States. In this context, the literature suggests that customers who source from firms subject to the program could face increased supply chain uncertainty, which translates into an incentive to pre-emptively rewire their supply chains outside of California in anticipation of future disruptions (Custodio, Ferreira, and Garcia-Appendini, 2023; Ersahin, Giannetti, and Huang, 2024). This uncertainty may be driven by suppliers subject to the program experiencing a higher loss of profitability, a decrease in economic activity, an incentive to shift production away from California to less productive plants (Bartram et al., 2022), or growing financial constraints (Ivanov et al., 2024). Alternatively, it may be driven by suppliers that pass through the costs of complying with the climate policy to their customers (Cludius, de Bruyn, Schumacher, and Vergeer, 2020).

To contextualize these drivers within the framework of the California cap-and-trade program, it is useful to analyze the 10-K forms of suppliers subject to the policy. Figure 1 illustrates the most frequent trigrams appearing in the sections of these records dedicated to discussions of the program. The figure reveals that, in these sections, treated suppliers primarily emphasize increased costs (in trigrams such as "increased compliance costs") and the pressure to decarbonize economic activity (in trigrams such as "GHG reduction initiatives").

They also express uncertainty (in trigrams such as “could negatively impact”) and refer to the possibility of passing costs on to final customers (in trigrams such as “cost contractual terms” or “recover increased costs”).

Suppliers affected by the California cap-and-trade program face multiple challenges, including the cost of emission allowances and a policy-induced increase in electricity and transportation costs (as of 2015). In addition, they face pressure to decarbonize production, which can lead to stranded assets, along with uncertainties surrounding policy adoption. For example, the filing of the climate change lawsuit *California Chamber of Commerce v. State Air Resources Board* at the time of the policy aimed to invalidate the program along with the auction of emission allowances.[6] In addition, firms face uncertainty about future compliance costs, although volatility in the price of emission allowances has been relatively low relative to other cap-and-trade programs, such as the EU ETS. Thus, uncertainty about the price of emission allowances probably plays a minor role, since the price of emission allowances remained close to its $10 floor during the initial phase of carbon trading, as shown by Fuchs, Stroebel, and Terstegge (2024). Overall, faced with the risk of future supply chain disruptions or higher input costs, downstream customers may have the incentive to switch to suppliers with lower exposure to climate transition risks.

The regulatory bodies overseeing the California cap-and-trade program recognize risks arising from uncoordinated climate actions in the United States. To mitigate risks of carbon leakage, the California cap-and-trade program provides exemptions for certain highly exposed entities. Fowlie et al. (2016) estimate the risk of carbon leakage in international trade flows due to incomplete climate policies affecting energy prices in California. This risk is particularly significant in the energy-intensive and trade-exposed industrial sectors. Moreover, 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

[6] In 2017, the California Supreme Court denied the petitions. For more details, see https://climatecasechart.com/case/california-chamber-of-commerce-v-california-air-resources-board/).

different climate policies (Fowlie, Petersen, and Reguant, 2021).[7]

Building on this conceptual framework, we conduct an empirical analysis 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.

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 otherwise similar 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 combined with a matching strategy, 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:

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

[7] 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 spillover channel, where higher carbon prices incentivize investment and innovation in low-carbon technologies, ultimately reducing emissions.

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 that reports emissions above 25,000 tons of CO2 equivalents at the beginning 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.

In our estimations, we compare treated suppliers to similar control suppliers based on a matching strategy, which we explain below. In addition, $X_{i,t}$ includes controls for suppliers' size (logarithm of total assets), profitability (return on assets, ROA, defined as the ratio of EBITDA to assets), leverage (total debt-to-assets ratio), Tobin's Q, and R&D stock (ratio of the sum of past R&D expenditures to assets). $z_{i,j,t}$ 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, customer fixed effects, and year fixed effects, or in our preferred specification, 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 before the implementation of the California cap-and-trade program. Assuming that the pre-program supply chain configuration of the firms was optimal, there would be little incentive for the firms to alter their supply chains before the program was implemented. 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 increased their emissions above the threshold before the program was implemented, our estimates would likely be attenuated.

Our main coefficient of interest is β. Including 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) who 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, in our preferred specification, the estimated difference in the probability of termination can be reasonably attributed to supply-side factors. If the program places affected suppliers at a disadvantage in relation 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' business relationships worldwide 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 scope 1 emissions 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 Revere using the parent company names provided by the EPA. When parent names do not match, we use facility names to 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 with FactSet Revere using FactSet IDs and PERMCO identifiers obtained through the Center for Research in Security Prices (CRSP).

Our initial (unmatched) sample consists of a panel of 360,735 supplier-customer pair-year observations from FactSet Revere spanning the period from 2010 to 2017. The sample includes suppliers whose financial information is available in Compustat and excludes supplier-customer pairs that end their relationship in the year in which one of the firms leaves the Compustat sample. This sample period enables us to analyze the evolution of supply chains starting from the beginning of the EPA emissions reporting (i.e., 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 2 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 and its direct competitors, such as Steel Dynamics, NUCOR, and AK Steel, supply Worthington Industries with products. In our preferred analysis, 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 (scopes 1 and 2) directly reported by firms drawn from the Carbon Disclosure Project (CDP).[8] The data also include emissions (scope 3) estimated by the ICE Climate Transition Finance team (formerly known as Urgentem).[9] We merge these data using suppliers' and customers' International Securities Identification Number (ISIN) codes. Among our sample suppliers, 501 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 related 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 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

[8] 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.

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

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 the time window of our study, three years before the implementation of the cap-and-trade program and up to four years after it, is adequate to capture both dynamic effects, and their persistence, while minimizing potential confounding factors.

3.4 Matched sample

Table 2 compares non-treated and treated firms in the initial sample, revealing significant differences across several observable characteristics. To account for these differences, we estimate equation (1) using a matched sample and apply various matching techniques. In our baseline approach, we match each treated supplier exactly by country (i.e., headquartered in the United States) and industry (using two-digit SIC codes), and employ a propensity score weighting approach based on pre-treatment size (total assets) and profitability (ROA). Each treated supplier is matched with at least three control suppliers using the nearest-neighbor algorithm, without replacement. In robustness tests, we demonstrate that our results are robust regardless of the matching approach used.

Figure 3 shows that the standardized differences in mean size and profitability are closer to zero after the 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, as shown in Table 1.

In an alternative matching approach, we compare treated suppliers with 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 supplier 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 identification assumptions and perform robustness checks to validate our baseline findings. Finally, we explore alternative interpretations for our baseline results.

4.1 Business relationship termination

Table 4 shows the results of the estimation of equation (1) in our baseline-matched sample with different sets of control variables. The regression in column (1) 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 than for control suppliers. 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.

One concern with the specification in column (1) is that the results could be driven by customer-specific shocks rather than suppliers' exposure to the cap-and-trade program. We address this concern by estimating an alternative specification with customer-by-year fixed effects, which absorbs customer-specific demand. These regressions absorb potential biases from unobservable customer-level shocks, thus improving our identification strategy. This setup allows for comparisons between treated suppliers and control suppliers that sell to the same customer in a given year. This requires restricting the sample to suppliers with at least two business relationships, reducing our sample by approximately 25%, since customers with only one supplier in a given year are excluded.

Restricting the estimation sample to customers with multiple suppliers could potentially overstate the estimates of our key coefficient. This is because such customers may find it relatively easier to discontinue their relationship with the treated supplier due to their pre-existing ties with alternative, non-treated suppliers. To mitigate this concern, we present the results for the restricted sample in column (2), employing the same specification as in column (1). The coefficient of the interaction term, $Treated \times Post$, is 0.079 and statistically significant at the 10% level, closely matching the estimate from column (1). This result suggests that the sample restriction does not introduce bias into our estimates.

In addition, column (3) presents the interaction term coefficient using the specification with customer-by-year fixed effects and the restricted sample. The coefficient is positive and statistically significant at the 1% level. Compared to column (2), this coefficient is lower at 0.061, confirming that failing to control for demand biases the estimates upward. Column (4) includes additional controls for suppliers and supplier-customer pairs. The coefficient in column (4) is our preferred specification and suggests that the cap-and-trade program increases the likelihood that a customer ends 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 12.8% increase relative to the standard deviation of this probability, which is 40% in the matched sample (see Table 3). Moreover, this coefficient corresponds to a 25% increase relative to the average unconditional probability of terminating a supplier relationship, which is 20% in the matched sample.

The magnitudes of the impacts of the climate transition risk on supply chain relationships that we document are in line with those observed in the literature that studies climate risks and supply chain relationships. Pankratz and Schiller (2023), for instance, estimate that suppliers exposed to heat days exceeding their customers' expectations are 28% more likely than other suppliers to experience the termination of pre-existing customer relationships in the same year relative to the unconditional probability of terminating relationships, which is 27% in their sample.

In column (5), we exclude from the estimate in column (4) all customers with facilities in California that emit 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 (4), 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 (4).

Last, in column (6), 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, corresponding to a 5.8% (= 0.023 / 0.40) increase relative to the standard deviation of the 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 4 displays the dynamic difference-in-differences effect 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 introduction of the policy, suggesting that there are no preexisting differential trends between treated and control suppliers. The figure also indicates that treated suppliers see an increase in the probability that their pre-existing customer relationships are 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. In 2017, after the termination of several treated supplier-customer relationships in 2014 and 2016, fewer treated supplier-customer relationships remained, making 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 from 2010 to 2017. Our identification strategy relies on the assumption that customers of the treated suppliers did not reconfigure their supply chains in anticipation of the cap-and-trade policy's implementation. Figure IA1 in the Internet Appendix shows that suppliers might have acted on their expectation of rising costs due to the cap-and-trade program by significantly increasing their inventories during the pre-treatment period between 2010 and 2012, relative to 2013. More importantly, Figure IA2 in the Internet Appendix 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 indicate that the rewiring away from suppliers subject to the cap-and-trade occurred 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 that treated suppliers experience termination of customer relationships compared to control suppliers. In this section, we test the robustness of our baseline results using alternative outcomes, 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 began new relationships with treated suppliers, our baseline results could 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 following years as long as the relationship is observed in FactSet Revere. 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 in a specification that excludes treated customers from the sample. The estimated coefficient is also negative, though not statistically significant, in the specification with supplier-by-competitor group and customer-by-year-by-competitor group fixed effects.

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 19.3% decrease relative to the standard deviation of the probability of initiating a supplier relationship, which is 45% in the matched sample. Overall, these findings reinforce our interpretation that supply chains were restructured to avoid the jurisdiction of the California cap-and-trade program.

Generalized difference-in-differences. If the cap-and-trade program drives the observed effects, we would expect the likelihood of terminating relationships with treated firms to be more pronounced for suppliers with higher emission 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, divided 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 IA1 in the

Internet Appendix reports positive and statistically significant coefficients for the interaction term, *Treatment Intensity*$\times$*Post*, indicating that the probability of terminating a relationship with a treated supplier increases with the intensity of the supplier's emissions in California. A one-standard-deviation increase in emissions intensity in California is associated with a 1.2 percentage point higher likelihood of terminating pre-existing customer relationships with treated suppliers compared to control suppliers.

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 beginning 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 IA2, Panel A, in the Internet Appendix indicates that our results remain robust to this alternative clustering approach, using the specification in column (4) of Table 4.

Alternative treatment dummy variable. In Table IA2, Panel A, 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 with control suppliers using the same matching and propensity score weighting approach as in the baseline estimation. In particular, 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.

Conditional logit. Table IA2 Panel A, column (3), 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-industry fixed effects. Due to computational constraints, we omit supplier fixed effects, and the regression is estimated on our matched baseline sample (using propensity score matching). The results are consistent with the baseline estimates, with the coefficient of interest remaining positive and statistically significant.

Alternative fixed effects. In our baseline analysis, we saturate the specification using supplier and customer-by-year fixed effects. Moreover, in our estimation, we account for the possibility of suppliers' industries 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' industries. Here, we perform a robustness test by including supplier industry-by-year fixed effects. Column (4) of Table IA2, Panel A, indicates that our results remain significant to include a different set of fixed effects.[10]

Supply chain turnover. Throughout our analysis, we focus on a large and representative sample of supplier-customer relationships and study the extensive margin of such relationships. However, we also perform a robustness test by replicating our analysis over a relatively

[10]The within-firm strategy mirrors approaches in the banking literature that compare banks for the same borrower to assess the impact of bank liquidity shocks (Khwaja and Mian, 2008). Ivashina et al. (2022) and Paravisini et al. (2023) highlight that this method assumes that credit demand is not specific to individual banks. In our context, this means that customer purchasing behavior is not tied to specific suppliers, which is more likely when suppliers belong to the same industry. Therefore, we incorporate supplier industry-by-year fixed effects to limit the variation to suppliers within the same industry.

smaller sample of significant supplier-customer relationships based on the Statements of Financial Standards 14 and 131, which require publicly listed U.S. firms to disclose the identity of their customers that represent at least 10% of their total sales.[11] Column (5) of Table IA2, Panel A, studies the intensive margin of these relationships by using the logarithm of the sales of a given supplier to each of its reported customers in a given year as a dependent variable. The estimates indicate that for each customer, sales from treated suppliers experience a greater drop than sales from control suppliers after the introduction of the cap-and-trade program. Column (6) studies the extensive margin of these major relationships and rejects the hypothesis that, in this sample, supply chains are more likely to rewire away following the cap-and-trade. Overall, this suggests that major relationships seem to become less important but are not more likely to terminate.

Suppliers geographically concentrated in California. Table IA2, Panel B, column (1), presents the estimates of the baseline specification after excluding geographically diversified treated suppliers from the sample. To identify these suppliers, we replicate the geographical diversification measure at the firm level used by Bartram et al. (2022). Suppliers 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 terminating a customer relationship compared to control suppliers. This suggests that our findings are not driven solely by the within-firm reallocation of production to facilities outside of California.

Financially unconstrained suppliers. Table IA2, Panel B, column (2), presents the estimates of the baseline specification for a sub-sample consisting exclusively of treated suppliers

[11] This data is available in the Compustat Segment database. We extract supply chain relationships for the period 2010–2017.

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 (i.e., firm size, dividend payout, short- and long-term debt rating, the index introduced by Kaplan and Zingales, 1997, the index introduced by Whited and Wu, 2006, and the index introduced by Hadlock and Pierce, 2010) calculated 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.

Placebo test. Table IA2, Panel B, column (3), presents the baseline results using an alternative treatment group. Suppliers are included in this placebo group if they have headquarters in California but do not have facilities in the state that emit more than 25,000 tons of equivalent CO2 in 2010. For instance, suppliers in this placebo group are "tech firms" headquartered in California such as HP Inc. and DSP Group. These placebo suppliers are matched to other non-treated suppliers using the same propensity score weighting approach employed in the baseline estimation. The results indicate that suppliers in the placebo 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.[12]

State-level shocks. In our baseline analysis, we saturate the specification using supplier

[12] 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 climate policy. As a result, their customers are less likely to have the incentive to reconfigure their supply chains away from these placebo-treated suppliers.

and customer-by-year fixed effects. In addition to these fixed effects, in Table IA2 Panel B, column (4), we present the baseline results including supplier headquarters' state-by-year fixed effects. This allows us to account for confounding macroeconomic shocks affecting suppliers at their headquarter locations, or California-specific shocks (e.g., higher inflation in California). Our results remain significant when we control for state-level (macroeconomic) shocks.

Spillover test. Table IA2, Panel B, column (5), presents the results for an alternative treatment group designed to test whether the introduction of the 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 the cap-and-trade. Specifically, these are suppliers that emit more than 25,000 tons of CO_2 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.[13] Suppliers in the baseline matched control group with significant emissions in these states (i.e., emissions exceeding 25,000 tons of CO_2 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, significantly restructure their supply chains preemptively, and the cap-and-trade program does not have a significant spillover effect on the control group.

[13]We thank von Meyerinck, Niessen-Ruenzi, Schmid, and 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.

Alternative control group. Table IA2, Panel B, column (6), presents the results for an alternative control group designed to test whether the baseline effects observed are driven by alternative events that could affect suppliers operating in California over the period 2010–2017. Therefore, the sample limits the matched control group to suppliers headquartered in California. Our results remain significant within this subsample.

Alternative matching approaches. Table IA3 of the Internet Appendix presents the results of the baseline specification estimated using an unmatched sample in column (1) and various alternative matching approaches in columns (2)-(6). Specifically, in column (2), we adopt an exact match on country and industry and propensity score matching with replacement based on pre-treatment size and profitability, where each treated observation is matched to at least three control observations based on the nearest neighbor algorithm. Due to the potentially repeated control observations, we saturate the specification using fixed effects at the matching group-by-year level.

Next, in column (3) we replicate the propensity score weighting method used in the baseline estimation, augmenting the set of matching controls to include suppliers' leverage. Column (4) 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 investment in innovation (R&D stock). Column (5) applies an exact match based on suppliers' country, industry and customer-year, along with a propensity score match using pre-treatment size and profitability. Using the nearest-neighbor algorithm, we select at least one control for each treated supplier. In column (6), we follow the same matching procedure as in column (5) but additionally weight the observations according to their propensity scores. Across all specifications, the estimated coefficients for 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.

5.1 Competitiveness channel

When faced with the introduction of climate policies that affect their suppliers, customers are arguably more likely to shift their supply chains away from suppliers exposed to climate transition risks when affected suppliers operate in more competitive industries. In such cases, customers can avoid possible supply chain disruptions arising from the suppliers' exposure to climate transition risks by selecting among a large number of substitute suppliers that are not subject to climate policies.

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, the *Treated* × *Post* coefficient is statistically and economically significant for suppliers operating in more competitive industries. In fact, the effects are more pronounced in less concentrated industries, industries with a lower Lerner Index, and industries with more competitors.

5.2 Switching costs

Switching costs may influence the restructuring of supply chains. Industries producing standardized inputs, which allow for easier substitution, are more likely to see the termination of business relationships when faced with increased physical climate risks (Barrot and Sauvagnat, 2016) or transition climate risks. Furthermore, 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 the characteristics of the supplier: differentiated vs. standardized goods, based on the two-digit SIC code classification proposed by Giannetti, Burkart, and Ellingsen (2011), and above-median vs. 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 same vs. different state as their suppliers) and the duration of the relationships (above vs. below median duration).

Consistent with the proposed economic mechanism, Panel A of Table 7 shows that the probability that treated suppliers experience the termination of customer relationships is concentrated among suppliers that produce standardized goods (column (2)) and those with a below-median investment in innovation as proxied by R&D stock (column (4)).[14] Establishing and maintaining customized supplier-customer relationships is costly, indicating that firms

[14]Notably, approximately 86% of the customers in our sample have at least one standardized supplier.

face important decisions regarding establishing or terminating these relationships. Panel B shows that the impact of the cap-and-trade program is stronger when switching costs are lower. This is evident in column (1), which compares treated suppliers to control suppliers located in the same state as their customers (as opposed to those in different states in column (2)), and in column (4), which focuses on relationships with below-median duration (as opposed to above-median duration in column (3)).

5.3 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 (see Section B of the Internet Appendix), the introduction of the 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:

$$Y_{i,t+1} = \beta_1 \; \mathit{Treated}_i \times \mathit{Post}_t + \beta_2 \; \mathit{Differentiated}_i \times \mathit{Treated}_i \times \mathit{Post}_t + \mu_i + \mu_{s(i),t} + \epsilon_{i,t}, \quad (3)$$

where $Y_{i,t+1}$ is the supplier's output (logarithm of revenues), the average 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). $\mathit{Differentiated}_i$ is a dummy variable that takes the value of one for suppliers that produce differentiated goods following Giannetti et al. (2011). The regressions include supplier fixed effects (μ_i) and supplier industry-by-year ($\mu_{s(i),t}$) fixed effects.

To match treated suppliers with non-treated counterparts, we use an exact match based on country (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.[15]

[15] 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.

Table 8 presents the results. Column (1) shows that the revenues of the treated suppliers are relatively lower by a statistically significant 11% after the introduction of the cap-and-trade program. Furthermore, column (2) shows that the reduction in revenues is about 15% and statistically significant among suppliers producing standardized inputs, while only 8.7% among suppliers producing differentiated 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 4.7 percentage points among those producing standardized inputs and statistically significant among those producing differentiated inputs. Although our measure does not directly capture suppliers' marginal costs, the observed increase in average COGS aligns with the anticipated cost increase due to the cap-and-trade program (e.g., costs associated with emission permits, monitoring and reporting 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 reduction of 35%.

Columns (7) and (8) show that suppliers of standardized inputs reduce the investment rate (measured as the change in PPE divided by total assets) by 2.5 percentage points. Additionally, columns (9) and (10) indicate a decline in profitability (ROA) for affected suppliers. This effect is particularly significant among suppliers of standardized goods, who see a reduction in profitability of 6.2 percentage points. Overall, these findings confirm that the cap-and-trade program negatively affected treated suppliers, especially when their customers face relatively low switching costs to alternative options. In contrast, suppliers in industries that produce differentiated goods appear to be more able to maintain customer relationships, helping to explain the observed differential effects between treated and control suppliers.

We conclude the analysis of the economic mechanisms underlying the rewiring of supply chains following the introduction of the program by investigating whether the climate 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 shocks' 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 into a customer-year panel, excluding customers directly affected by the cap-and-trade and estimate the following regression model:

$$Y_{j,t+1} = \beta \mathit{Has\ Treated\ Supplier}_j \times \mathit{Post}_t + \eta_j + \eta_{s(j),t} + \epsilon_{j,t}, \tag{4}$$

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). $\mathit{Has\ Treated\ Supplier}_j$ is a dummy variable that takes the value of one if customer j has at least one treated supplier after the introduction of the program 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 η_j and industry-by-year fixed effects $\eta_{s(j),t}$.

Table 9 presents the results. We find that customers exposed to treated suppliers do not experience a significant decrease in revenues or an increase in the average cost of sales. Furthermore, these affected customers do not reduce their assets, cut investments, 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.

5.4 Customers' climate transition risks

We have presented evidence that competitiveness in product markets 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 affected suppliers to potentially benefit from reductions in their scope 3 emissions.

To test this hypothesis, we analyze sub-samples of customers above vs. below the pre-treatment industry-level median of climate change attention, as measured by Sautner et al. (2023).[16] 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 less environmental awareness.

We further investigate this issue using alternative firm-level proxies for exposure to climate transition risks. In columns (3) and (4), we examine the effects within sub-samples of customers headquartered in states classified as Democrat or Republican based on the 2016 presidential elections, and in columns (5) and (6) for states that are either members or non-members of the U.S. Climate Alliance coalition (as of 2017). These measures serve as proxies for the sensitivity to these states' environmental issues, particularly climate transition risks. Our estimates in columns (3) and (4) confirm that the rewiring of the supply chain is concentrated among customers headquartered in Republican states, which generally exhibit lower sensitivity to environmental issues. 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.

[16] 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 are available at: `https://osf.io/fd6jq`.

6 Environmental effects

This section explores the environmental implications of supply chain-driven carbon leakage resulting from uncoordinated climate action.

We construct emission measures at the firm and supply chain level to perform this analysis. We aggregate each supplier's facility-level emissions data from the EPA database for all U.S. facilities for the firm-level measures. We then create a measure of the emission intensity, defined as total emissions normalized by the firm's assets. We obtain U.S.-wide EPA emissions data for 501 suppliers included in FactSet Revere between 2010 and 2017. As an alternative measure of firm-level emission intensity, we rely on scope 1 and scope 2 emissions intensity (normalized by revenues) reported by firms drawn from CDP.

For the supply chain-level emissions, for each customer in our sample, we use our supply chain linkages data to compute the average U.S.-wide direct supply chain emission intensity (i.e., the average emission intensity of the direct suppliers of each customer). As an alternative measure for supply-chain emissions, we use the scope 3 emission intensity (normalized by revenues) estimated by the ICE Climate Transition Finance team.

Our self-constructed measures have some limitations compared to emissions data from commercial data providers. The primary drawback is that they only partially capture the total emissions firms produce. This limitation arises because our data are 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, Raghunandan, and Rajgopal, 2024), which researchers often rely on due to the limited availability of comprehensive corporate scope 3 emissions reporting.[17]

We first use these data to examine the environmental impact of the 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 *Treated* × *Post* interaction estimates from equation (3), where $Y_{i,t+1}$ represents the measures of emissions of the treated suppliers. In column (1), the dependent variable is the supplier's U.S.-wide emission intensity that we calculate using the 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. If anything, they indicate a higher U.S.-wide emission intensity following the program implementation. These effects are only statistically significant using the U.S.-wide emissions from the EPA. Overall, this evidence suggests that emission intensity did not decline 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 business 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 the ICE Climate Transition Finance.

The coefficient of the interaction *Treated* × *Post* is positive and significant in both columns (1) and (2). Thus, our findings indicate that customers who have business relationships with treated suppliers exhibit a significant deterioration in their environmental performance

[17] 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 direct suppliers. In contrast, upstream scope 3 emissions, as inferred by data providers, account for emissions produced throughout the entire supply chain of a customer. Additionally, these inferred scope 3 emissions are scaled by the volume of goods and services a customer purchases from each supplier.

(proxied by emission intensity) in the supply chain. This evidence suggests that the cap-and-trade policy in an uncoordinated climate action setting may have unintentionally driven a shift toward supply chains with greater environmental impact. 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 energy sources in these regions, which are not subject to the same carbon pricing constraints.

We estimate the differential carbon footprint of supply chains rewired away from the cap-and-trade program by comparing customers affected by this rewiring to "counterfactual" customers whose supply chains remained linked to suppliers subject to the program. Supporting our interpretation that uncoordinated climate action led to a shift toward more polluting supply chains, Table IA4 in the Internet Appendix shows that, following the introduction of the program, the average U.S.-wide emission intensity of rewired supply chains is relatively higher.

7 Conclusion

Over the past decades, many countries have implemented climate 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 than suppliers not subject to the program. 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 more 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. In addition, 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 in an uncoordinated climate action setting. Our analysis shows that suppliers affected by the cap-and-trade program do not report reductions in direct emission intensity; if anything, emissions increase. Furthermore, we observe a worsening of the carbon footprint of the supply chain among customers indirectly affected by their supply chains. Taken together, these findings highlight that carbon leakage can partially undermine the intended positive environmental impacts of climate policies.

Our paper highlights the implications of a lack of coordination in climate policies on production networks. In the context of the EU ETS, similar concerns have led to the introduction of a Carbon Border Adjustment Mechanism. Although a comparable policy might not be feasible in the context of U.S. industrial production networks, our paper contributes to the ongoing discussion on the need for more coordinated climate action worldwide.

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Table 1: Summary Statistics on Unmatched Sample

	Mean	Std. Dev.	Median	Minimum	Maximum	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
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's 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
Relationship duration (years)	3.16	2.61	2.00	1.00	15.00	360,735
Panel B: Supplier-Year Data						
Treated	0.01	0.12	0.00	0.00	1.00	36,588
Revenues (billion $)	4.97	13.90	0.54	0.00	95.21	36,055
COGS/Assets	0.61	0.68	0.40	0.00	3.81	30,488
Total assets (billion $)	11.60	40.06	0.85	0.00	308.85	36,118
ΔPPE/Assets	0.02	0.11	0.00	-0.24	0.67	30,273
ROA	0.01	0.38	0.09	-2.33	0.53	30,430
U.S. 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
Revenues (billion $)	4.78	12.99	0.63	0.00	88.63	29,062
COGS/Assets	0.59	0.67	0.38	0.00	3.71	24,660
Total assets (billion $)	11.51	39.29	1.11	0.00	307.29	29,131
ΔPPE/Assets	0.02	0.10	0.00	-0.21	0.61	24,507
ROA	0.01	0.36	0.09	-2.18	0.51	24,629
Average supplier emission intensity	148.86	300.82	29.38	0.00	1,796.33	7,295
Scope 3 emission intensity	66.90	110.24	26.79	0.04	713.47	4,176

This table presents the mean, standard deviation, median, minimum, maximum and number of observations for the main variables of interest. 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 statistics for supplier-year and customer-year observations in our base sample, respectively. The sample period is from 2010 to 2017. All continuous variables are winsorized at the 1 and 99% level. Refer to Table A1 in the Appendix for variable definitions.

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's 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 presents means for non-treated and treated supplier groups and t-tests for the difference between the groups for the main variables of interest. The sample period is from 2010 to 2017. Standard errors are in parenthesis. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table 3: Summary Statistics on Matched Sample

	Mean	Std. Dev.	Median	Minimum	Maximum	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
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's 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
Relationship duration (years)	3.46	2.79	2.00	1.00	15.00	112,677

This table presents the mean, standard deviation, median, minimum, maximum and number of observations for the main variables using the matched sample. Treated suppliers are matched to control suppliers based on country (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 (ROA). Each treated supplier is matched without replacement to a minimum of three control suppliers using the nearest neighbor algorithm. The sample period is from 2010 to 2017. All continuous variables are winsorized at the 1 and 99% level. Refer to Table A1 in the Appendix for variable definitions.

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

	(1)	(2)	(3)	(4)	(5)	(6)
Treated × Post	0.082*	0.079*	0.061***	0.051**	0.047**	0.023**
	(0.046)	(0.045)	(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's 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	Yes	
Matched supplier competitor group						Yes
Excl. treated customers					Yes	
Year FE	Yes	Yes				
Supplier FE	Yes	Yes	Yes	Yes	Yes	
Customer FE	Yes	Yes				
Customer × Year FE			Yes	Yes	Yes	
Supplier × Competitor group FE						Yes
Customer × Year × Competitor group FE						Yes
Observations	110,048	83,129	83,129	76,220	71,140	112,370
R^2	0.317	0.335	0.832	0.839	0.844	0.833

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. In column (5), customers that produce emissions above 25,000 tons of CO2e in California in 2010 are excluded. In column (6), each treated supplier is compared to all of its direct competitors over the entire sample period. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering in columns (1)-(5) and supplier-by-competitor group and competitor group in column (6) are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

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's 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
Observations	110,048	83,129	76,220	71,140	112,370
R^2	0.395	0.857	0.860	0.866	0.865

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (2). The dependent variable *Beginning* is a dummy variable that takes the value of one if the supplier-customer relationship starts in a given year, and zero if the relationship is observed in FactSet and persists since the previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. 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. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. 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 the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table 6: Probability of Termination and Cap-and-Trade Program: Competitiveness Channel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	HHI		Lerner Index		HHI Competitor Group		Number of Competitors	
	High	Low	High	Low	High	Low	Low	High
Treated × Post	0.008	0.095***	0.017	0.091***	0.010	0.037***	0.014	0.035**
	(0.021)	(0.032)	(0.023)	(0.035)	(0.012)	(0.010)	(0.011)	(0.014)
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
Observations	43,102	26,360	48,152	21,976	48,079	64,291	52,438	59,932
R^2	0.873	0.835	0.861	0.745	0.845	0.821	0.826	0.837

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. In columns (1) and (2), suppliers are in a sector with average pre-treatment SIC three-digit HHI above or below the median, respectively. In columns (3) and (4), suppliers are in SIC three-digit sectors with average pre-treatment Lerner Index above or below the median, respectively. In columns (5) and (6), suppliers are in a group of matched competitors with average pre-treatment HHI above or below the median, respectively. In columns (7) and (8), suppliers have a mean pre-treatment number of matched competitors in their group below or above the median, respectively. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering are in columns (1) to (4) and for supplier-by-competitor group and competitor group level clustering in columns (5) to (8) are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table 7: Probability of Termination and Cap-and-Trade Program: Switching Costs

Panel A: Input Specificity				
	(1)	(2)	(3)	(4)
	Good Type		R&D Stock	
	Differentiated	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
Observations	41,947	21,002	38,537	31,395
R^2	0.893	0.828	0.840	0.857
Panel B: Relationship Strength				
	(1)	(2)	(3)	(4)
	Distance Control Supplier-Customer		Relationship Duration	
	Same State	Different State	High	Low
Treated × Post	0.138***	0.042**	-0.036	0.052*
	(0.053)	(0.020)	(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
Observations	8,855	70,002	19,729	50,853
R^2	0.899	0.849	0.859	0.869

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. Columns (1) and (2), Panel A, are based on suppliers producing differentiated or standardized inputs, respectively (according to the classification provided by Giannetti et al., 2011). Columns (3) and (4), are based on suppliers with an average R&D over total assets throughout the pre-treatment period above or below the median, respectively. Columns (1) and (2), Panel B, include pairs where control suppliers and customers are headquartered in the same or different state while keeping the sample of treated suppliers unchanged. Columns (3) and (4), are based on pairs having a relationship duration in year t above or below the median relationship duration of the entire sample, respectively. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Revenues (log)		COGS/Assets		Total Assets (log)		ΔPPE/Assets		ROA	
Treated × Post	-0.108**	-0.146**	0.003	0.047**	-0.193***	-0.354***	-0.025**	-0.024*	-0.048***	-0.062***
	(0.045)	(0.061)	(0.016)	(0.020)	(0.052)	(0.060)	(0.012)	(0.013)	(0.011)	(0.015)
Differentiated × Treated × Post		-0.059		-0.087***		0.238***		0.019		0.044**
		(0.071)		(0.026)		(0.070)		(0.013)		(0.017)
Matched supplier	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Supplier industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,442	8,747	10,815	9,081	10,869	9,121	10,811	9,084	10,803	9,071
R^2	0.980	0.983	0.869	0.871	0.984	0.986	0.452	0.418	0.797	0.807

This table presents difference-in-differences estimates of matched supplier-level panel regressions using equation (3). The dependent variable in 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 columns (7) and (8), it is the yearly change in PPE over lag of total assets; in columns (9) and (10) it is EBITDA over lag of total assets. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. *Differentiated* is a dummy variable that takes the value of one for suppliers in industries that produce differentiated goods, and zero otherwise (according to the classification provided by Giannetti et al., 2011). The sample consists of FactSet Revere suppliers with financial information sourced from Compustat in the 2010-2017 period. Each treated supplier is matched without replacement to a minimum of one control supplier using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions.
* $p<.10$; ** $p<.05$; *** $p<.01$.

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

	(1) Revenues (log)	(2) COGS/Assets	(3) Total Assets (log)	(4) ΔPPE/Assets	(5) ROA
Has treated supplier × Post	0.009	-0.018	0.014	-0.004	-0.008
	(0.034)	(0.017)	(0.033)	(0.004)	(0.017)
Matched customer	Yes	Yes	Yes	Yes	Yes
Customer FE	Yes	Yes	Yes	Yes	Yes
Customer industry × Year FE	Yes	Yes	Yes	Yes	Yes
Observations	19,041	19,564	19,688	19,390	18,114
R^2	0.975	0.901	0.980	0.442	0.698

This table presents difference-in-differences estimates of matched customer-level panel regressions using equation (4). 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 total 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. *Has Treated Supplier* is a dummy variable that takes the value of one for customers that have at least one treated supplier after the introduction of the cap-and-trade program. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. The sample consists of FactSet Revere customers with financial information sourced from Compustat in the 2010-2017 period. Customers directly affected by the California cap-and-trade program are excluded from the sample. Each customer with at least one treated supplier subject to the program is matched without replacement to a minimum of one customer having no treated suppliers using propensity score weighting based on an exact match on industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for customer-level clustering are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table 10: Probability of Termination and Cap-and-Trade Program: Customers' Climate Transition Awareness

	(1)	(2)	(3)	(4)	(5)	(6)
	Climate Change Awareness		Political Party		U.S. Climate Alliance	
	High	Low	Democrat	Republican	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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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
Observations	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

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. Columns (1) and (2) are based on customers with relatively high or low average pre-treatment attention to climate change relative to the median computed at the SIC two-digit and headquarters' country level (Sautner et al., 2023 construct the proxy for customers' attentiveness to climate change. Columns (3) and (4) are based on customers with headquarters in democratic or republican states as per their 2016 elections, respectively. Columns (5) and (6) are based 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). The sample is based on supplier-customer pair-year observations from FactSet Revere spanning the period from 2010 to 2017. It includes suppliers whose financial information is available in Compustat and it excludes supplier-customer pairs that end their relationship in the year in which one of the firms exits the Compustat sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

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 industry × Year FE	Yes	Yes
Observations	2,186	900
R^2	0.953	0.982

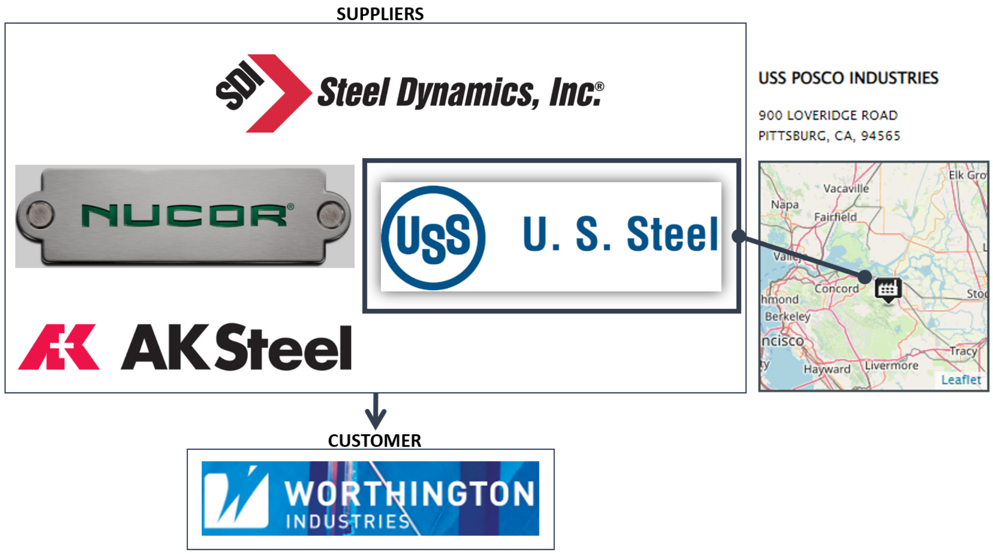
Panel B: Supply Chain Emissions		
	(1)	(2)
	Average Supplier Emission Intensity	Scope 3 Emission Intensity
Has treated supplier × Post	43.973***	29.073***
	(13.985)	(11.205)
Matched customer	Yes	Yes
Customer FE	Yes	Yes
Customer industry × Year FE	Yes	Yes
Observations	5,200	2,626
R^2	0.919	0.738

This table presents difference-in-differences estimates of matched supplier-level panel regressions using equation (3), in Panel A, and difference-in-differences estimates of matched customer-level panel regressions using equation (4), in Panel B. The dependent variable in column (1), Panel A, is a firm's U.S.-wide emissions intensity. The dependent variable in column (2), Panel A, is a firm's CDP reported scope 1 and 2 emission intensity. The dependent variable in column (1), Panel B, is the average U.S.-wide emission intensity of each customer's supplier. In column (2), Panel B, it is the ICE Climate Transition Finance inferred scope 3 upstream emission intensity. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Has Treated Supplier* is a dummy variable that takes the value of one for customers that have at least one treated supplier after the introduction of the cap-and-trade program. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. In Panel A, the sample consists of FactSet Revere suppliers with financial information sourced from Compustat in the 2010-2017 period. Each treated supplier is matched without replacement to a minimum of one control supplier using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. In Panel B, the sample consists of FactSet Revere customers with financial information sourced from Compustat in the 2010-2017 period. Customers directly affected by the California cap-and-trade program are excluded from the sample. Each customer with at least one treated supplier subject to the program is matched without replacement to a minimum of one customer having no treated suppliers using propensity score weighting based on an exact match on industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier or customer-level clustering, in Panels A and B respectively, are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Figure 1: Frequency of Trigrams associated with the California Cap-and-Trade Program in affected Suppliers' 10-K Forms

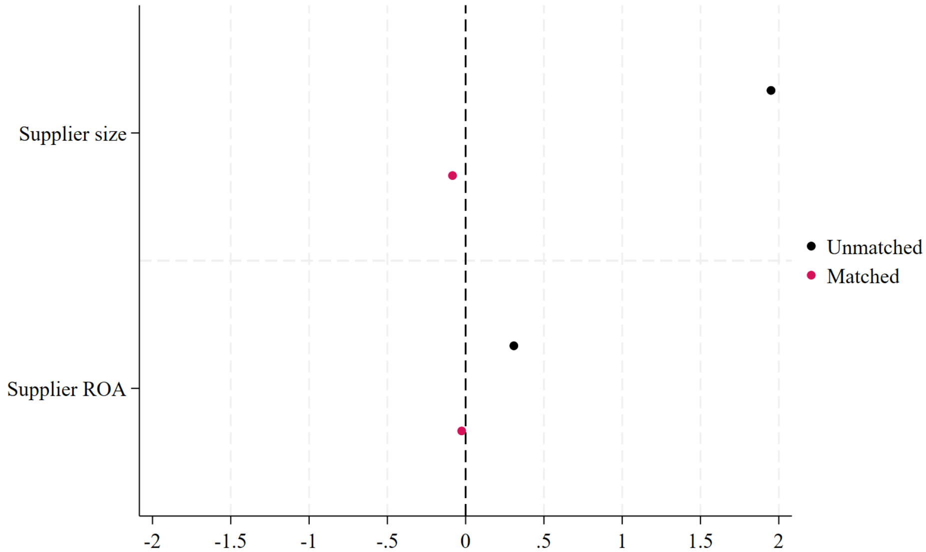
This figure illustrates the 30 most frequent trigrams that appear in the SEC 10-K Forms filed by treated suppliers in 2013 and 2014, specifically focusing on the paragraphs that discuss the cap-and-trade program. The size of each trigram is proportional to the number of times it is mentioned across the filings.

Figure 2: Illustration of the Structure of the Data



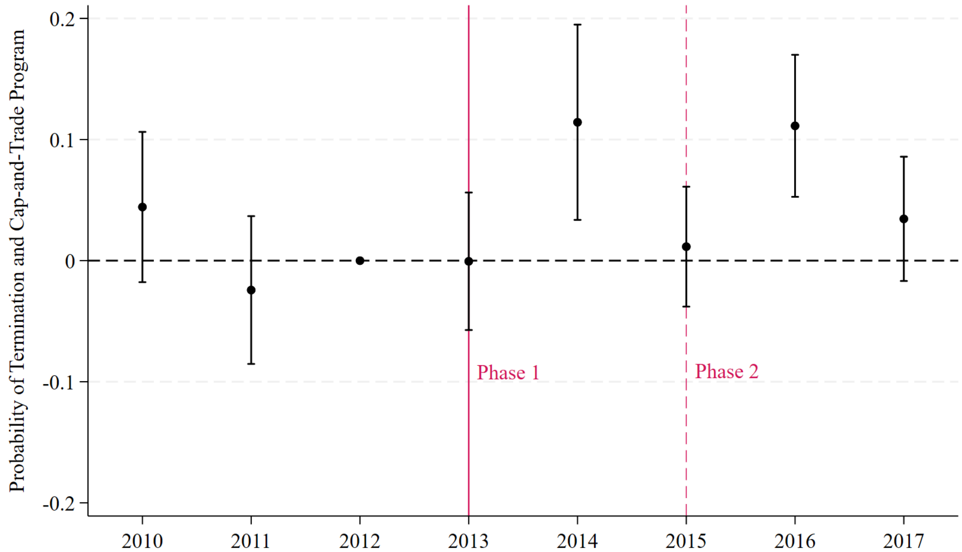
This figure illustrates the structure of the dataset through the example of the treated supplier U.S. Steel and its customer Worthington Industries. According to the EPA FLIGHT data, the U.S. Steel POSCO facility mapped close to San Francisco on the right-hand side of the figure produced sufficient emissions 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 3: Matching Performance



This figure presents the standardized difference in mean between control and treated groups and the performance of the propensity score weighting estimator.

Figure 4: Probability of Termination around Cap-and-Trade Program



This figure shows the difference and 95% confidence intervals in the probability of termination of a business relationship between treated and control suppliers around the introduction of the Californian cap-and-trade program in 2013 using the specification in column (4) of Table 4. The program targeted electricity generation and industrial facilities emitting more than 25,000 tons of carbon dioxide (CO2) equivalents annually in 2013. The program was expanded to include petroleum and natural gas distributors in 2015. Treated suppliers are defined as firms with at least one facility in California reporting emissions exceeding 25,000 tons of CO2 equivalents in 2010. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on industry and nearest neighbor algorithm on firm size, and profitability. Standard errors are adjusted for supplier-level clustering.

Appendix

Table A1: Variable Definitions

Variable	Definition
Ending	Dummy variable that takes the value one if the relationship between supplier i and customer j is not observed in year $t+1$, and zero if the relationship is observed in year t and continues into $t+1$ (FactSet Revere).
Beginning	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 following years as long as the relationship is observed (FactSet Revere).
Relationship duration	Duration (in years) of the relationship from the first time in which the customer-supplier pair is observed (FactSet Revere).
Treated	Dummy variable that takes the value of one if the supplier produced more than 25,000 tons of CO2 equivalents in one of its California facilities in 2010, and zero otherwise (EPA, FactSet Revere).
Has treated supplier	Dummy variable that takes the value of one if the customer has at least one supplier including and after 2013 that has produced at least 25,000 tons of CO2 equivalents in its California facilities in 2010, and zero otherwise (EPA, FactSet Revere).
Supplier total assets	Total assets in billion \$ (Compustat (AT)).
Supplier ROA	Ratio of earnings before interest, taxes, depreciation, and amortization to total assets (Compustat EBITDA / AT).
Supplier leverage	Long-term debt plus debt in current liabilities, divided by total assets (Compustat (DLTT + DLC) / AT).
Supplier Tobin's Q	Tobin's Q (Compustat (AT + Market Value − BE) / AT where Market Value = CSHO × PRCC F).
Supplier R&D stock	Ratio of stock of research and development (R&D) computed as the sum of R&D expenses from 2005 to year t, assuming R&D expenditures are zero when the observation is missing, divided by total assets (Compustat $\sum_{t=2005}^{t} XRD\ /\ AT$).
Supplier revenues	Total revenues in billion \$ (Compustat REVT).
Supplier COGS / Assets	Ratio of cost of goods sold to lagged total assets (Compustat COGS / AT).
Supplier ΔPPE / Assets	Change in supplier property, plant, and equipment in levels, divided by lagged total assets (Compustat ΔPPE / AT).
Supplier U.S. emission intensity	Total emissions produced by the supplier in its EPA facilities located in the U.S., divided by total assets (EPA, FactSet Revere, Compustat).
Scope 1-2 emission intensity	Scope 1-2 emissions reported by the supplier, divided by revenues (ICE Climate Transition Finance, CDP).

(Continued)

Table A1: Variable Definitions - *Continued*

Variable	Definition
Customer total assets	Total assets in billion \$ (Compustat AT).
Customer ROA	Ratio of earnings before interest, taxes, depreciation, and amortization to total assets (Compustat EBITDA / AT).
Customer leverage	Long term debt plus debt in current liabilities, divided by total assets (Compustat (DLTT + DLC) / AT).
Customer revenues	Total revenues in billion \$ (Compustat REVT).
Customer COGS / Assets	Ratio of cost of goods sold to lagged total assets (Compustat COGS / AT).
Customer ΔPPE / Assets	Change in customer property, plant, and equipment in levels, divided by lagged total assets(Compustat ΔPPE / AT).
Average supplier emission intensity	Average U.S. emission intensity of the suppliers of each customer (EPA, FactSet Revere).
Scope 3 emission intensity	Scope 3 emissions inferred by the data provider and associated with the goods and services used by the firm, divided by revenues (ICE Climate Transition Finance).

Internet Appendix for

Rewiring Supply Chains Through Uncoordinated Climate Policy

A Robustness

Table IA1: Probability of Termination and Cap-and-Trade Program: Treatment Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment intensity × Post	0.012***	0.009**	0.012***	0.012**	0.011**	0.003*
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.002)
Treated × Post					0.022	
					(0.023)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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					
Customer × Year FE		Yes	Yes	Yes	Yes	
Supplier × Competitor group FE						Yes
Customer × Year × Competitor group FE						Yes
Observations	110,048	83,129	76,220	71,140	76,220	112,370
R^2	0.320	0.833	0.840	0.845	0.840	0.833

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treatment Intensity* is the ratio of each supplier's California emissions in 2010 and its total assets. This value is then standardized by its standard deviation. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. In column (4), customers that report emissions above 25,000 tons of CO2e in California in 2010 are excluded. In column (6), each treated supplier is compared to all of its direct competitors over the entire sample period. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. Each treated supplier is matched without replacement to a minimum of three control suppliers using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for supplier-level clustering in columns (1)-(5) and supplier-by-competitor group and competitor group in column (6) are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table IA2: Probability of Termination and Cap-and-Trade Program: Robustness

Panel A						
	(1) Cluster by Pair	(2) Treated Supplier 2012	(3) Conditional Logit	(4) Supplier Ind.-Year FE	(5) Segments Sales (log)	(6) Sample Ending
Treated × Post	0.051***		0.387***	0.033**	-0.210*	-0.052
	(0.013)		(0.097)	(0.015)	(0.113)	(0.064)
Treated 2012 × Post		0.025*				
		(0.014)				
Controls	Yes	Yes	Yes	Yes		
Matched supplier	Yes	Yes		Yes	Yes	Yes
Matched sample			Yes			
Supplier FE	Yes	Yes		Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Supplier industry FE			Yes			
Supplier industry × Year FE				Yes		
Observations	76,220	70,903	48,862	76,218	4,457	4,457
R^2	0.839	0.889		0.848	0.973	0.670

Panel B						
	(1) Geographically Concentrated	(2) Financially Unconstrained	(3) Placebo California	(4) Supplier HQ State-Year FE	(5) Spillover	(6) California Suppliers
Treated × Post	0.049*	0.055**		0.045***		0.094***
	(0.025)	(0.028)		(0.016)		(0.035)
HQ California × Post			-0.005			
			(0.016)			
U.S. Climate Alliance × Post					-0.022	
					(0.042)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
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
Observations	69,327	49,647	138,702	76,204	5,880	17,336
R^2	0.760	0.868	0.527	0.850	0.770	0.906

This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). *Treated* takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* takes the value of one in 2013 and subsequent years, and zero otherwise. Where not specified, the dependent variable is *Ending* (it takes the value of one if the supplier-customer relationship ends in a given year, and zero if it persists), the sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data in Compustat over the 2010-2017 period, and treated suppliers are matched to control suppliers as described in Section 3. In Panel A, column (1) standard errors are clustered at the pair level. In column (2), the treatment is allocated according to firms' 2012 emissions in their Californian facilities. In column (3), the model is a conditional logit with bootstrapped standard errors using the sample underlying column (3), Table 4. Column (4) includes supplier industry-by-year fixed effects. Columns (5) and (6) are based on the Compustat Segment sample. The dependent variable in column (5) is the logarithm of the sales between the pair in a given year. In Panel B, column (1), treated suppliers are not geographically diversified. In column (2), treated suppliers are financially unconstrained, using the composite financial constraint indicator proposed by Bartram et al. (2022). In column (3) the placebo group consists of non-treated firms headquartered in California. Column (4) includes supplier headquarters' state-by-year fixed effects. In column (5), the treatment group consists of control suppliers whose 2010 emissions in U.S. Climate Alliance States (as of 2017) are above 25,000 tons of CO2 equivalents, following von Meyerinck et al. (2021). In column (6), the control group only includes suppliers with headquarters in California. Robust standard errors adjusted for pair-level clustering in Panel A column (1) and for supplier-level clustering in the remaining specifications are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table IA3: Probability of Termination and Cap-and-Trade Program: Matching Robustness

	(1) Unmatched Sample	(2) PSM with replacement	(3) PSW with Leverage	(4) PSW with Financials	(5) PSM within Customer-Year	(6) PSW within Customer-Year
Treated × Post	0.029**	0.029*	0.072***	0.074***	0.034**	0.043***
	(0.014)	(0.017)	(0.022)	(0.023)	(0.016)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Matched sample		Yes	Yes	Yes	Yes	Yes
Supplier FE	Yes	Yes	Yes	Yes	Yes	Yes
Customer × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Match group × Year FE		Yes				
Observations	248,709	89,528	76,220	72,222	50,606	50,497
R^2	0.373	0.457	0.844	0.832	0.414	0.582

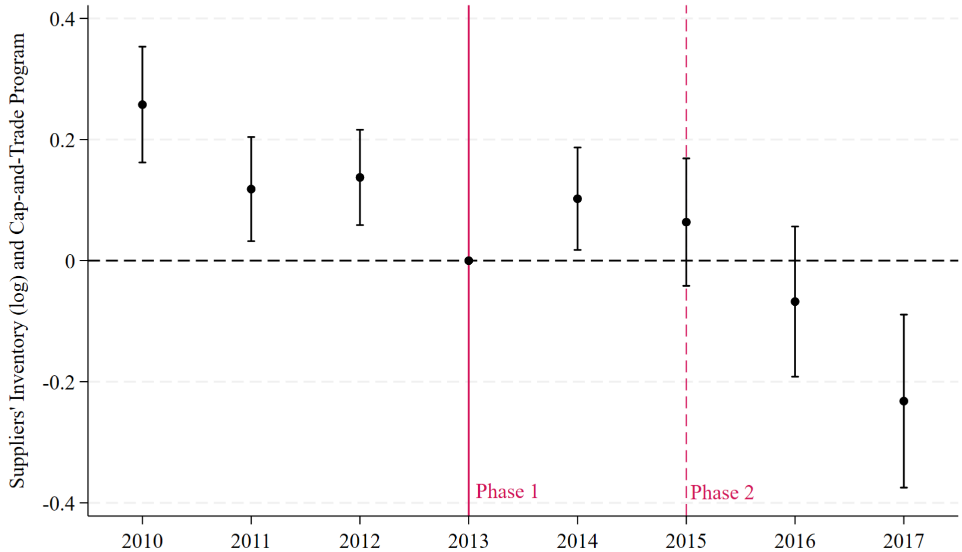
This table presents difference-in-differences estimates of matched customer-supplier-level panel regressions using equation (1). The dependent variable *Ending* is a dummy variable that takes the value of one if the supplier-customer relationship ends in a given year, and zero if the relationship persists in both the current and previous year. *Treated* is a dummy variable that takes the value of one for suppliers that have at least one facility in California reporting emissions above 25,000 tons of CO2 equivalents in 2010. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. *PSW* stands for propensity score weighting, *PSM.* stands for propensity score matching. The sample consists of supplier-customer pair-year observations from FactSet Revere, with corresponding supplier financial data sourced from Compustat, in the 2010-2017 period. Supplier-customer pairs that terminate their relationship in the same year that either firm exits the Compustat sample are excluded from the sample. In column (1), the regression is estimated on an unmatched supplier-customer pair-year panel from 2010 to 2017. In column (2), we match observations using an exact match on country, industry and a propensity score matching approach with replacement based on size and profitability. In column (3), we use an exact match on suppliers' country, industry and a propensity score weighting approach based on suppliers' pre-treatment size, profitability and leverage. 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 (4) we expand the previous propensity score weighting approach to additionally include suppliers' Tobin's Q, R&D stock and cash. In column (5), we use an exact match based on suppliers' country, industry 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 without replacement. In column (6), 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. Robust standard errors adjusted for supplier-level clustering are reported in parentheses. In column (2) they are clustered at the supplier-match group-level. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

Table IA4: Environmental Effects of Cap-and-Trade Program on Supply Chains

	Average supplier emission intensity
Rewired supply chain	-139.952**
	(61.071)
Rewired supply chain × Post	133.616**
	(66.988)
Customer FE	Yes
Customer industry × Year FE	Yes
Observations	2,323
R^2	0.853

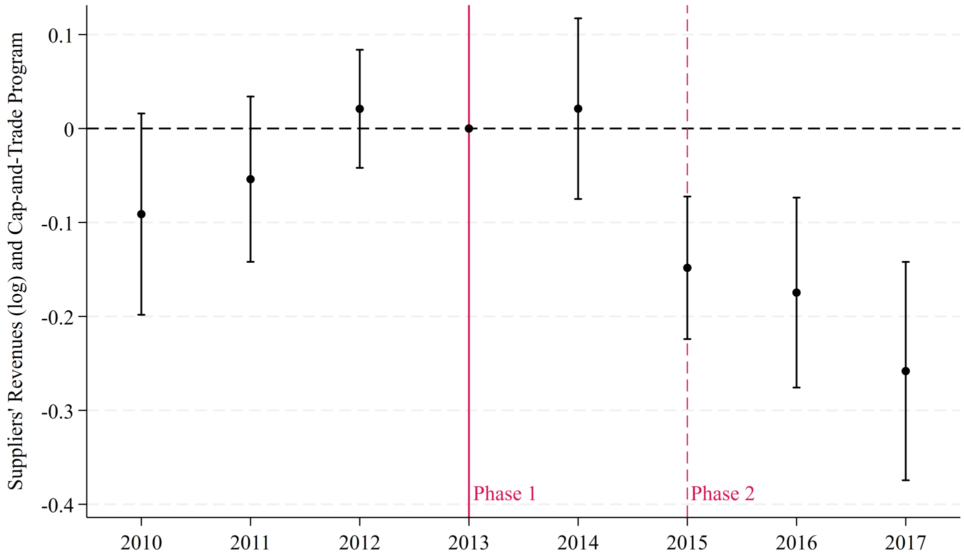
This table presents difference-in-differences estimates of matched customer-level panel regressions. The dependent variable is the average U.S. supply chain emission intensity of a given customer i in year t. *Rewired Supply Chain* is a dummy that takes the value of one if a customer sources its inputs from a supply chain that is rewired away from the cap-and-trade in a given year (i.e., if that year, the customer has fewer treated suppliers than in the previous year), and zero otherwise. *Post* is a dummy variable that takes the value of one in 2013 and subsequent years, and zero otherwise. The sample consists of FactSet Revere customers with financial information sourced from Compustat in the 2010-2017 period. Customers directly affected by the California cap-and-trade program are excluded from the sample. Each customer with at least one treated supplier subject to the program is matched without replacement to a minimum of one customer having no treated suppliers using propensity score weighting based on an exact match on industry and nearest neighbor algorithm on firm size, and profitability. Robust standard errors adjusted for customer-level clustering are reported in parentheses. Refer to Table A1 in the Appendix for variable definitions. * $p<.10$; ** $p<.05$; *** $p<.01$.

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



This figure shows the difference and 95% confidence intervals in the logarithm of inventories between treated and control suppliers around the introduction of the Californian cap-and-trade program in 2013. The program targeted electricity generation and industrial facilities emitting more than 25,000 tons of carbon dioxide (CO2) equivalents annually in 2013. The program was expanded to include petroleum and natural gas distributors in 2015. The sample consists of FactSet Revere suppliers with financial information sourced from Compustat in the 2010-2017 period. Each treated supplier is matched without replacement to a minimum of one control supplier using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on size, and profitability. Standard errors are adjusted for supplier-level clustering.

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



This figure shows the difference and 95% confidence intervals in the logarithm of revenues between treated and control suppliers around the introduction of the Californian cap-and-trade program in 2013. The program targeted electricity generation and industrial facilities emitting more than 25,000 tons of carbon dioxide (CO2) equivalents annually in 2013. The program was expanded to include petroleum and natural gas distributors in 2015. The sample consists of FactSet Revere suppliers with financial information sourced from Compustat in the 2010-2017 period. Each treated supplier is matched without replacement to a minimum of one control supplier using propensity score weighting based on an exact match on country, industry and nearest neighbor algorithm on size, and profitability. Standard errors are adjusted for supplier-level clustering.

B Anecdotal Evidence

In this section, we provide anecdotal evidence suggesting that uncoordinated climate actions in the United States, following the implementation of the California cap-and-trade program, expose affected suppliers to climate transition risks. The following excerpts are sourced from an analysis of 10-K filings by these suppliers.

I. Air Products and Chemicals

In this excerpt, the supplier warns that the cap-and-trade program and the uncertainty related to future climate policies can constitute a source of climate transition risk. The risk can negatively affect the firm's financial performance.

"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`).

II. California Steel Industries

In this excerpt, the supplier refers to uncoordinated climate policies across different jurisdictions as a source of climate transition risk that might place the firm at a disadvantage relative to competitors operating in countries with no climate policies in place.

"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`).

III. Campbell Soup Company

In this excerpt, the supplier mentions that exposure to climate policies might affect its supply chain due to possible disruptions to its facilities.

"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`).

IV. Freeport-McMoRan Copper & Gold Inc

In this excerpt, the supplier states that the exposure to climate policies might negatively affect its performance by reducing the demand for its products.

"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`).

V. United States Steel

In this excerpt, the supplier states that the heterogeneous exposure to climate transition risks of firms belonging to the same group of competitors, due to globally uncoordinated climate action, might affect its financial performance.

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`).

VI. USG

In this excerpt, the supplier states that the firm might be unable to pass through the costs resulting from the introduction of climate policies.

"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`).