Climate Innovation and Carbon Emissions: Evidence from Supply Chain Networks

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Abstract

We examine the role of climate innovation in reducing firms' carbon emissions along supply chain networks. Using a large panel of U.S. firms, we find that climate innovation of suppliers causally reduces carbon emissions of downstream customers, driven by product innovations, on both the intensive margin (existing customers) and the extensive margin (newly acquired customers). A one standard deviation increase in the supplier's climate patent ratio reduces direct emissions by approximately 11% over the next five years for existing customers and similarly for new customers. Moreover, we find that customers, particularly those with strong decarbonization incentives, actively reconfigure their supply chains in favor of suppliers with climate patents, especially after they obtain high-value patents. Various identification strategies combine instrumental variables (state-level R&D tax subsidies and examiner busyness) with a difference-in-differences design and exogenous shocks from supplier mergers. Our results underscore that climate innovation not only directly reduces emissions but also fosters the formation of new supply chains that amplify the knowledge diffusion effect.

Keywords: climate innovation, carbon emissions, supply chain network, business stealing, supply chain formation

JEL Classifications: L14, O31, O33, Q54, Q55

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Abstract

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1 Introduction

It is widely assumed that climate innovation will play a central role in the global transition to climate neutrality.[1] However, the incentives to develop new climate technologies are encumbered by two fundamental market failures: social benefits typically exceed the private return to innovators, and lack of incentives to adopt technologies given that existing policies, such as carbon taxes or regulations, internalize global climate externalities only imperfectly.[2] In spite of these obstacles, there is significant production of climate patents: the US Patent and Trademark Office (USPTO) has classified more than 100,000 patent grants to US public-listed firms after 2000 as climate-related, amounting to about 5% of the total flow of patent grants in recent years.[3] But is there evidence that climate innovation actually has a meaningful and measurable impact on greenhouse gas (GHG) emissions? The micro-level research on this question finds no evidence, but it has focused on emissions of innovators.[4] We argue that climate innovation is typically embedded in products and hence most emission benefits should accrue at the customers that use the innovator's products. Therefore, we look at supply chain networks to study the decarbonization effect of climate innovation. We present empirical evidence that climate innovation diffuses through supplier–customer relationships, leading to emission reductions and reshaping firm networks.

We organize our analysis into two parts. First, we demonstrate that climate innovation by upstream suppliers causally reduces the carbon emissions of downstream customers — both through an intensive margin (existing customers) and an extensive margin channel (newly acquired customers).

[1] In its influential transition scenarios to net zero by 2050, the International Energy Agency estimates that half of the reductions in 2050 will come from new technologies that currently exist only as prototypes and are not yet used at scale (IEA, 2021).

[2] The first issue is prominent in the economics of innovation literature (see Arrow, 1962; Griliches, 1991; Hall, Mairesse, and Mohnen, 2010, for a survey), while the second also applies to other environmental externalities (Gillingham, Newell, and Palmer, 2009).

[3] Starting in 2010, after an appeal from the UNFCCC (United Nations Framework Convention on Climate Change), the USPTO and the European Patent Office (EPO) launched and progressively expanded the joint Y02/Y04S tagging scheme to identify climate-related patents, which we use in our paper. The number of patents classified by the USPTO under this scheme as climate-related increased sharply until 2015 and has since maintained a fairly stable level (EPO, 2015; Angelucci, Hurtado-Albir, and Volpe, 2018).

[4] Bolton, Kacperczyk, and Wiedemann (2023), the only firm-level analysis, document that climate-related patents have no significant impact on innovators' carbon emissions, regardless of the time horizon considered and whether for renewables, clean energy, or fossil energy efficiency. Bolton et al. (2023) attribute this finding to a rebound effect or Jevons paradox (Jevons, 1865), the idea that energy savings may simply induce a larger demand for energy. However, they focus on carbon emissions of innovating firms and possible technology spillovers to peer firms, where they also find no effect. They also find no effect on innovators' Scope 3 emissions and neither do we, as we discuss below.

Second, we show that customers, and in particular customers with heightened incentives to reduce emissions, respond to this innovation by selectively matching with climate-innovating suppliers. Thus, our analysis reveals a two-step pattern of knowledge diffusion: climate innovation not only improves emission outcomes but also alters supply chain formation by attracting new customers.

To start, we explore the intensive margin of emission reductions — the impact on existing supply chain networks. To analyze the emission impact in supply chain networks, we identify important customers using the FactSet Revere supply chain and the Compustat customer segment database and construct a supplier $\times$ customer $\times$ year sample by merging these data with data on patents, firm and product characteristics, and carbon emission data. Using panel regressions, we find that more climate patents of suppliers lead to subsequent reductions in CO_2 emissions of customers. We find this effect consistently for Scope 1 (direct) and Scope 2 (indirect) emissions, and for total emissions (tons of CO_2) as well as for emission intensities (total emissions divided by firm output).[5] The effect is economically meaningful. For example, an increase in the supplier's climate patent ratio by one standard deviation reduces Scope 1 emissions of the customer by about 10.7% and emission intensity by about 12.5% over the next five years. The effect is robust when we look at climate patent counts instead of patent ratios. Since our focus is on product innovations, we identify product patents following Bena, Ortiz-Molina, and Simintzi (2022). We find that almost 70% of climate patents are product innovations, and show that the emission effect is essentially driven by product patents; when we apply the same analysis to climate patents granted for process innovations, we find very weak effects. To the best of our knowledge, we are the first to provide firm-level evidence that climate patents generate actual GHG emission reductions.

We also investigate the technology areas that generate the highest emission impact and study the role of directed technological change. We find that patents in energy, buildings and transportation are the most important, and that "green" (rather than "grey") technology has the biggest impact.

Importantly, we confirm this finding within a panel of stable supplier–customer relationships by estimating specifications with supplier–customer pair fixed effects. These fixed effects allow us to isolate the within-supply chain variations, effectively controlling for the selection channel. Throughout our intensive margin analysis, we consistently account for this high-dimensional fixed effect structure, which also serves as an initial step to mitigate concerns about selection bias —

[5] This distinction matters in light of concerns about rebound effects. Also, total emissions and emission intensity often deliver inconsistent results (Bolton and Kacperczyk, 2021a, 2022; Lioui and Misra, 2023).

specifically, the possibility that firms with a stronger decarbonization agenda may be more likely to match with climate-innovative suppliers.

Our causal interpretation of the effect of climate innovation on emission reductions builds on two separate identification strategies. First, we use US state-level R&D tax credit changes to instrument for the number of climate patents produced. Our identification assumption is that, conditional on firm-level controls and fixed effects, changes in state-level R&D tax credits affect customer emissions only through the impact on supplier climate innovation. Thus, in our design, the supplier and customer do not operate in the same state. In the first stage, we document that the number of climate patents strongly increases following a hike in tax subsidies (non-climate patents also increase). In the second stage, we confirm that (instrumented) climate patents significantly reduce customer emissions. Our second identification strategy focuses on patent quality by using patent examiner busyness as a random variation in the thoroughness of patent approvals which is associated with patent lower-quality (Shu, Tian, and Zhan, 2022). We document that climate patents tainted by elevated examiner busyness have a weaker effect on downstream emission reductions.

Next, we turn to the extensive margin — the emission effect on new supply chain relationships. We compare emission outcomes for newly acquired versus existing customers. We find that having a supplier with climate patents reduces Scope 1 emissions of newly acquired customers by 11% over a five-year horizon, compared to a 4%–5% reduction among existing customers, suggesting a stronger decarbonization effect along the extensive margin.

While the analysis of the extensive margin channel of innovation in supply chains is novel, it comes with its own endogeneity challenges. Supply chains are not randomly reconfigured, as firms with more ambitious climate goals may be more likely to choose new suppliers with stronger climate innovation credentials (and in fact they do, as we show below). Thus, the endogeneity issues are in fact quite similar to those in the intensive margin analysis. To address this concern, we need to identify a subsample of customer firms for which exogenous shocks alter the climate innovation potential of their supplier networks. To do so, we exploit supply chain disruptions triggered by corporate mergers of suppliers. From the customers' perspective, they are typically exogenous events outside their control. Specifically, when a supplier firm is acquired, it ceases to exist as an independent entity but its plants typically continue to operate and to often serve its existing customers (due to switching costs), inducing a switch by default in the customer's supply chain to a new corporate decision-maker (the acquirer) that may pursue a different climate innovation agenda. We deploy a difference-in-differences framework that contrasts outcomes across successful and failed mergers to exclude confounding effects associated with the merger event. The elevated frequency of merger bids among listed US firms in the last 20 years allows us to identify a large sample of acquisition bids, both successful and unsuccessful, that create a plausibly exogenous shock to the supplier's propensity for climate innovation. We find that customers experience statistically and economically meaningful emission reductions after such a merger-induced exogenous switch in their supply chain if the new supplier entity (the acquirer) is an active climate innovator.

Having shown that the emission effects of climate patents are plausibly causal (they occur after exogenous shocks in the climate innovativeness of suppliers), we turn to the dynamics of supply chain connections. We provide evidence that customers actively seek out climate innovators as their new suppliers, *after* they have obtained new climate patents. In other words, we establish that there is an additional "business stealing" channel in the emission impact of climate technologies.[6] Our findings in the first part establish that innovation matters for emission reductions; our second part shows that customers recognize and act upon this. From an economic perspective, this two-step pattern — innovation causes emission impact, which then drives sorting in supply chains — matters as it allows for an understanding of the knowledge diffusion of climate technology and shows that reductions in downstream CO_2 emissions go beyond those observed in existing supply chains.[7]

We explore this idea in a series of approaches: we investigate customer firms' selection among potential suppliers, we analyze suppliers' success in attracting new customer firms, and we study the transmission channels that are most important for the formation of new supply chains, by looking at heterogeneity among customer firms and climate patents.

Our first approach uses a discrete choice model (McFadden, 1974) of customer firms' selection among a set of potential suppliers. For each customer-year with at least one recorded supply chain relationship, we create a set of potential suppliers consisting of the actual supplier and firms with similar products according to Hoberg and Phillips (2016)'s text-based product descriptions and network industry classification (TNIC). Our regression analysis shows strong evidence that

[6]While "business stealing" is an important concept in the innovation literature (Cohen, 2010) and highly relevant for the dynamics of supply chains (Pankratz and Schiller, 2021), the role of innovation in attracting new customers has not been formally studied in the supply chain literature.

[7]Our findings also offer validation for the often-expressed expectation that climate technologies will be widely adopted, as assumed e.g. in the IEA (2021) scenarios.

customers have a significant preference for suppliers with climate innovation. Specifically, an increase in the interquartile range of the climate patent ratio is associated with a 12% increase in the probability of selecting a supplier. Moreover, we observe that this preference is stronger for customer firms with higher environmental scores or higher initial carbon emissions.

We next examine suppliers' capacity for business expansion. Our regression analysis shows that climate innovation enables suppliers to attract new business customers. Specifically, an interquartile-range increase in a supplier's climate patent ratio is associated with a 7.45% to 22.1% increase in the number of new customers acquired between 2011 and 2021. These results indicate that customers actively respond to climate innovation, further reinforcing the economic significance of our findings on emissions reduction.

Next, we investigate transmission channels for the capacity to attract new customers. We find that new customer firms with with high GHG emissions or high environmental ratings (considered to be a proxy for a firm's climate mitigation and environmental preferences)[8] are more likely to switch to suppliers offering products that embed climate innovation. We use the patent examiner lottery as an instrument to control for any confounding effects in our evidence on transmission channels.

We also delve into the types of climate patents that have the strongest impact on the acquisition of new customers. We find that climate patents with higher market value, measured following Kogan, Papanikolaou, Seru, and Stoffman (2017), and with a tighter link to the supplier's core products have a stronger appeal. Since the innovation literature lacks an effective measure to link patents to products of innovators (Argente, Baslandze, Hanley, and Moreira, 2020), we develop a novel text-based measure that uses natural language processing, following methodology used in Kogan, Papanikolaou, Schmidt, and Seegmiller (2021), to compute pairwise document similarity (cosine similarity) between a given patent text and the product description from the company's 10-K annual report to determine the extent to which a patent is critical for the firm's core products. In our regression analysis, we observe that climate patents with a higher similarity score have a more pronounced impact on the acquisition of new customers.

[8] Corporate environmental, social and governance (ESG) preferences, often proxied by ESG ratings, are typically attributed to firms' belief in "doing well by doing good" (Baron, 2001), the impact of investors, or personal preferences of CEOs and board members (Bénabou and Tirole, 2010). Likewise, climate action by high-emission firms could be explained by pressure from climate-conscious institutional investors (Atta-Darkua, Glossner, Krueger, and Matos, 2022) and concerns about higher costs of capital (Bolton and Kacperczyk, 2021b).

Interestingly, these effects are significantly different from zero mostly only in the post-2010 period. The literature documents a dramatic increase in the public attention to climate change (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022) and a widening valuation gap between high-emission and low-emission firms around 2010 (Choi, Gao, Jiang, and Zhang, 2022), often attributed to the unexpected failure of the COP15 meeting in Copenhagen 2009, but there were also concomitant initiatives to enhance the impact and visibility of climate patents, including the USPTO Green Technology Pilot Program and the "Y02/Y04S" tagging scheme (EPO, 2015). Indeed, we show in event studies following Kogan et al. (2017) that there is a positive jump in the value of climate patents after 2010, but no comparable effect in the value of general patents.

Finally, we explore whether the acquisition of new customers has an impact on the operating performance of climate innovators. This is not a foregone conclusion since the higher revenue from "business stealing" may be offset by higher R&D investments and operating costs. We find an unambiguously positive effect on sales but an increase in returns on assets and mark-ups only after 2010, suggesting that only after the 2010 structural break did climate innovation command sufficient pricing power to compensate for the higher outlays.

Literature: By presenting the first micro-level evidence on the link between climate patents and emission reductions, our paper contributes to three topics in the literature. First, our paper is related to the growing literature on climate and green innovation and its determinants and effects. Dechezleprêtre, Glachant, Haščič, Johnstone, and Ménière (2011) document the dynamics, distribution, and international transfer of patented climate change mitigation technologies between 1978 and 2005. Aghion, Dechezleprêtre, Hémous, Martin, and Van Reenen (2016) construct firm-level panel data on auto industry innovation distinguishing between "dirty" and "clean" patents. They show that firms tend to innovate more in clean (and less in dirty) technologies when they face higher tax-inclusive fuel prices. Acemoglu, Aghion, Barrage, and Hémous (2020) find that the shale gas boom was associated with a decline in innovation in green relative to fossil fuels-based electricity generation technologies. Cohen, Gurun, and Nguyen (2021) document that firms in the energy sector produce many green patents in spite of receiving low environmental ratings. Dalla Fontana and Nanda (2022) show that climate patents granted to venture capital-backed firms are more likely to cite fundamental science and to be subsequently cited. In a comprehensive and global analysis of the emission effects of climate patents that also distinguishes between green and energy-augmenting technology, Bolton et al. (2023) document that climate innovation is path-dependent and has no significant impact on the future carbon emissions of innovators (Scope 1, 2 and 3), their peers or industries. Our analysis shares many details with their study and complements it by looking at customer firms. The literature is inconclusive concerning firm valuation effects: while Kuang and Liang (2022) show that high carbon-risk firms with little climate innovation underperform relative to more innovative peers and Reza and Wu (2022) show that firms' exposure to environmental regulation and regulatory risk positively affect the value of green innovation, Andriosopoulos, Czarnowski, and Marshall (2022) find no evidence that investors value green innovation. We contribute to this literature by linking climate patents to supply chains, identifying emission reduction effects at the customer level and a role for innovators and for customers in the technology diffusion.

Second, our paper is closely related to recent work on climate change concerns and the supply chain. Schiller (2018) and Dai, Liang, and Ng (2021b) show that ESG policies of customer firms can propagate to supplier firms, but not vice versa. HomRoy and Rauf (2023) show that supply chain connections influence the adoption of climate-responsible policies. More specifically, Deng, Duan, Li, and Pu (2023) show that major customers induce significant reductions in their suppliers' carbon emissions, in particular when they have emission-reduction commitments, lower switching costs or stronger bargaining power, and face higher climate regulatory risk. Pankratz and Schiller (2021) find that customers are more likely to terminate existing supplier-customer relationships if suppliers suffer from severe climate physical risks. Similarly, Bisetti, She, and Žaldokas (2023) show that U.S. firms cut imports and are more likely to terminate a trade relationship when their international suppliers experience environmental and social incidents. On the other hand, Dai, Duan, Liang, and Ng (2021a) provide evidence that firms outsource part of their carbon emissions to foreign suppliers. We contribute to this literature by showing that climate patents also create new supply chain links, by demonstrating the real emission impact of climate-related technologies in both new and existing supply chains, and by widening the perspective from the focus on customer motives with the finding that suppliers expand their customer base and sales.

Third, our paper is related to a small literature on corporate innovation in supply chains. Delgado and Mills (2020) show that firms in supply chain industries are more innovative than firms in business-to-consumer industries. Isaksson, Simeth, and Seifert (2016) show that buyer innovation in supply chain networks leads to more supplier innovation. Chu, Tian, and Wang (2019) find that customer geographic proximity increases supplier innovation. Todo, Matous, and Inoue (2016) find that Japanese suppliers with more distant knowledge improve productivity more than neighboring suppliers. At the industry level, Dong, Liu, Tang, and Qiu (2023) find that innovation of upstream industries in China positively impacts customer innovation. More specifically focusing on green innovation in supply chains, Chen, Wang, and Zhou (2019) argue in a theoretical analysis that suppliers and customers can increase environmental benefits and profits by cooperating on R&D strategies, and Costantini, Crespi, Marin, and Paglialunga (2017) present industry-level evidence that innovative activities have an impact on sector-level environmental performance in the innovating sector and in downstream sectors. We contribute to this literature the analysis that innovation allows suppliers to attract new customers which to our knowledge has not been documented before, and the firm-level analysis of emission benefits of innovation in supply chains.

The paper is organized as follows. Section 2 contains our data strategy, main variables and summary statistics. Section 3 presents the analysis of the intensive margin channel and Section 4 of the extensive margin channel. Section 5 studies new customer acquisition effects of climate technologies. The final section concludes.

2 Data and Sample Construction

2.1 Sample of Climate Patents

For our baseline patent sample, we start with the US patent database maintained by Leonid Kogan and coauthors of all US patents through 2021 that can be matched to CRSP-Compustat firms. The dataset is an updated version of the patent sample used in Kogan et al. (2017).[9] We then extend this sample to the most recently granted patents by extracting raw data from PatentsView.org and repeating Kogan et al. (2017)'s matching algorithm to match newly granted patents after 2021 to CRSP-Compustat firms.[10] We also obtain the Cooperative Patent Classification (CPC) codes from PatentsView.org to identify all patents that are climate-related. We use the "Y02" tag to identify climate patents, the tagging scheme launched jointly by the European Patent Office (EPO) and

[9]We are grateful to Leonid Kogan and coauthors for providing this dataset.

[10]Our extension to patents granted in 2022 and 2023 aims to partially mitigate the well-known patent truncation bias described in Lerner and Seru (2021), which is particularly important for climate patents given their recent nature. We find that many patents filed at the end of our sample (2018 - 2020) have not yet been granted, resulting in a significant drop in the number of patents at the end of the sample.

the USPTO in 2010 under the auspices of the United Nations Framework Convention on Climate Change to extend the reach of climate technologies to a wider range of stakeholders (Angelucci et al., 2018; Calel, 2020).[11] Our final patent sample includes 1,892,073 U.S. patents issued to CRSP Compustat firms with patent application dates from 2000 to 2020. Of these, 114,851 patents are classified as climate patents. Specifically, we search for the presence of a "Y02" tag in the CPC codes of a given patent.[12] Figure 1 provides an example of our identified climate patents.

Table A1 shows the annual number of climate-related patents sorted by patent application year. We further divide climate patents into climate process patents and climate product patents, following the method for general patents developed by Bena et al. (2022) and Ma (2022). A patent is classified as a process patent if its first claim (usually the most important claim) begins with the words "a process of," "a method of/for," and so on. Close to 31% of climate patents are process patents. Table A1 further tabulates the annual number of climate patents by "Y02" categories. Y02E (Energy) and Y02T (Transportation) are the two largest categories, accounting for nearly 60% of total climate innovation, and product innovation clearly dominates in these categories (as shown in Table A1 Panel B).

2.2 Supply Chain Data

The supply chain literature overwhelmingly uses two data sources to identify supply chain networks. First, companies must report all major customers (defined as purchasing more than 10% of their total sales) in their 10-K filing, and these data are compiled in the Compustat Customer Segment data. Second, the FactSet Revere Supply Chain dataset records a much larger set of supply chain relationships (about ten times larger) that FactSet compiles from a diverse range of sources, including conference call transcripts, capital market presentations, company press releases, company websites, etc., in addition to companies' 10-K filings (Zhao, Webster, and Luo, 2015). Following Schiller (2018) and Dai et al. (2021b), we merge both databases as our baseline sample. Each supply-chain data point contains information such as the names and company identifiers of the supplier and customer, the start and end date of the relationship, and sales. We require suppliers

[11] We exclude the Y02A (climate adaptation) and Y04S (smart grids) tags as they comprise very few patents.

[12] While the Y02 tagging scheme was only introduced in 2010, the tag was applied ex post to older patents and can be usefully exploited after 2000. It was initially limited to energy production (Y02E) and GHG capture and storage (Y02C), but later extended to transportation (Y02T), buildings (Y02B), production of goods (Y02P), and IT-related patents (Y02D).

and customers to be in the CRSP-Compustat sample. Furthermore, following Barrot and Sauvagnat (2016), we consider that firm A is a supplier to firm C in all years ranging from the first to the last year in which A reports C as one of its customers.

Table 1 reports the summary statistics at the supply-chain level. Panel A shows that we can identify 73,477 unique supply-chain relationships from 2003 to 2021.[13] When we require that customers have ESG ratings recorded in at least one of the three ESG databases (Refinitiv, Sustainalytics, and S&P Global), this number drops to 48,563. Furthermore, 43% of the relationships last fewer than three years. Panel B reports data for the subsample that contains sales information for the supplier-to-customer sales. This is a much smaller subsample, consisting of only approximately 12% of the supplier-customer relationships in the full sample, and it largely coincides with the data obtained from 10-K filings where sales reporting is mandatory. This subsample is used in our baseline regression since it allows for the most accurate measurement of the variable of interest.

Panel C of Table 1 tabulates bivariate distributions for suppliers' and customers' industries, with industries measured by NAICS at the 2-digit level and all frequencies greater than 2% highlighted. In Panel C, the most frequent supply-chain relationships are between suppliers in metal, machinery and equipment manufacturing (33) and customers in the same industry group (33), accounting for 12.47%. The second largest group is the information-to-information supplier-customer relationship.

2.3 Carbon Emissions and Environmental Ratings Data

We obtain firm-level CO_2 emission data from S&P Trucost. Trucost provides CO_2 emissions data for global-listed companies based on the Greenhouse Gas Protocol that sets the standards for measuring corporate emissions. Scope 1 emissions are direct emissions from operations that are owned or controlled by the reporting company. Scope 2 emissions are indirect ones from the generation of purchased or acquired electricity, steam, heating, or cooling consumed by the reporting company. We only use Scope 1 and Scope 2 emissions in our main analysis and exclude Scope 3 emissions.[14]

Furthermore, to investigate which types of business customers are attracted by climate innova-

[13]The FactSet Revere begins its supply-chain data in 2003.

[14]Scope 3 emissions "are the result of activities from assets not owned or controlled by the reporting organization, but that the organization indirectly affects in its value chain" (US EPA), i.e. indirect emissions not included in Scope 2. There is evidence of strong bias in Scope 3 emission data, see Section 3.2.

tion, we obtain environmental ratings for customer firms from three ESG ratings data providers: LSEG ESG (formerly Refinitiv ESG, and originally Asset4), Sustainalytics, and S&P Global ESG rating. Following Brandon, Glossner, Krueger, Matos, and Steffen (2020), we create a composite environmental score based on these three distinct environmental evaluations in order to maximize the sample coverage.[15]

2.4 Summary Statistics

In our analysis of customer emissions in Section 3, we focus on the customer × year sample, which requires that each customer firm has at least one reported CRSP-Compustat supplier in a given year. When there are multiple suppliers, we use the supplier-to-customer sales as weights to compute a weighted average measure of all suppliers (e.g., suppliers' climate patent ratio). We also require that the customer firm reports CO_2 emission data in S&P Trucost and that at least one supplier continues to sell products to the given customer for the next three years.[16]

As shown in Table 2, Panel A, our sample of customers is relatively small (2,831 observations) as we impose quite restrictive sample filters: sales between suppliers and customers must be reported, i.e. supply chain relationships without sales are dropped. This filter is important to obtain the most accurate estimate of our main variable of interest, the sales-weighted average climate innovation of all suppliers of a customer firm, considering that on average, each customer has 4.7 suppliers in a given year.[17] We set the climate patent ratio equal to zero if a supplier has no patent in a given year and find that the average climate patent ratio is 1.6%, suggesting that most suppliers contribute little to climate innovation. In the subsample in which we require that suppliers file at least one general patent (the denominator is non-zero), the mean of the climate patent ratio increases to 6%. In this sub-sample, the average number of general patents for suppliers is 11.20, while the average

[15] More specifically, we transform those raw environmental scores into three standard z-scores with a mean equal to zero and a standard deviation equal to 1. We then take the equal-weighted average for k z-scores conditional on the fact that there are k non-missing environmental scores for that firm:

$$Score_{i,t} = \frac{1_{A4,it} \times z_t(Score\_A4_{it}) + 1_{S\&P,it} \times z_t(Score\_S\&P_{it}) + 1_{Sus,it} \times z_t(Score\_Sus_{it})}{1_{A4,it} + 1_{S\&P,it} + 1_{Sus,it}}, \tag{1}$$

where $1_{A4,it}$ is an indicator variable equal to 1 if firm i is covered in LSEG ESG in year t.

[16] This filter is helpful when we investigate the long-term and stable supplier-customer relationships.

[17] We drop this sample filter in a complementary analysis in Section 3.

number of climate patents is 0.64.[18] Finally, the annual average (median) Scope 1 CO_2 emissions of a typical customer are 446,858 tons (387,327 tons) (the table records logs).

In Section 5 (when we examine whether climate innovation helps to attract new business customers), we focus on a sample of potential suppliers. Specifically, we require that each firm has at least one new customer firm in the sample between 2005 and 2021 (we exclude the financial sector and retail, and wholesale distribution). New customers are firms that have never bought the supplier's products or services before and start the supplier-customer relationship in the given year. Table 2, Panel B, reports summary statistics for this sample of potential suppliers. On average, each firm has 0.4 new customers and 2.52 existing customers in a fiscal year (the table records logs).

3 Intensive Margin: Emissions of Existing Customers

3.1 Main Results

In this section, we explore whether climate innovation by suppliers has an impact on reducing GHG emissions of existing customer firms along the supply chain. This analysis complements the work of Bolton et al. (2023) who primarily focus on the potential CO_2 emission reductions achieved by the innovating firms themselves. We argue that the primary beneficiaries of climate innovation should be the customers who buy products incorporating new climate technology, the innovating firms themselves. This idea is relevant in light of our finding in Table A1 that almost 70% of US climate patents are granted for product innovations. It is important to recognize that our analysis of customer emissions is limited as we exclusively focus on business customers. We do not have a reliable methodology to track GHG emissions of retail customers or the business customers of the innovator's direct customers. Consequently, the total CO_2 emissions savings should often be larger than what our study captures.

We construct a customer-firm × year sample following the procedures in Section 2.4. In particular, we require that each of the customer firms has at least one supplier in a given year. We run

[18] This figure differs from the summary statistics in Table 2, Panel A, because the variable in the table takes the natural logarithm. The climate patent ratio is lower (but in the same order of magnitude) than the mean green patent ratio (11%) reported in Bolton et al. (2023) for worldwide patents.

the following regressions on this sample,

$$\Delta_{t,t+k} \ln(\text{Emissions}_i) = \beta \text{Supplier's Climate Patent Ratio}_{i,t} + \gamma \mathbf{X}_{i,t} + \delta_{\text{NAIC-4},t} + \varepsilon_{i,t} \tag{2}$$

where the dependent variable $\Delta_{t,t+k} = \ln(\text{Emissions}_{i,t+k}) - \ln(\text{Emissions}_{i,t})$ measures the forward-looking change in GHG emissions for customer firm i from year t to $t+k$. We use four distinct measures for customer emissions, by distinguishing between Scope 1 (direct) and Scope 2 (indirect/energy-related) emissions and by calculating total emissions (tons of CO_2) and emission intensity (emissions divided by firm output) according to Bolton and Kacperczyk (2021a, 2022).[19]

We follow Bolton et al. (2023) and use the climate patent ratio to measure suppliers' climate innovation efforts, as the ratio captures the relative effort of climate innovation in the firm's total R&D output. As in Bolton et al. (2023), our main independent variable, supplier's climate patent ratio, is defined as the number of new climate patents divided by the number of new general patents, both counted in year t when the patent application was filed.[20] If there are multiple suppliers for this customer, we use the sales between each supplier and the given customer as weights and calculate the weighted average of the climate patent ratio. $\mathbf{X}_{i,t}$ includes firm size, Tobin's q, cash, book leverage, ROA, capital expenditure, sales growth and PPE. Besides, we also control for the number of suppliers as well as the CO_2 emissions in year t. In addition, notably to account for decarbonization trends at the industry level, we introduce industry-year fixed effects. We do not include firm fixed effects since our dependent variable is already differenced. Standard errors are clustered at the customer-firm level.

Table 3 presents our first main result. In Panel A, we consider Scope 1 emissions. We standardize the supplier's climate patent ratio so that it has a standard deviation of 1 and multiply the coefficients by 100 for readability. As shown in Panel A, a one-standard deviation increase in the supplier's climate patent ratio corresponds to a reduction of roughly 10.84% in total emissions (Scope 1) and 12.38% in emission intensity (Scope 1) after five years. Interestingly, the effect in-

[19] In the calculation of outputs, all values are expressed in 2000 real terms, using the US CPI deflator. We calculate the output following Kogan et al. (2017).

[20] Bolton et al. (2023) argue that patenting activity is driven by a firm's innovation capacity and that new climate patent filings should be related to a firm's total innovation capacity to get an accurate picture of the intensity of climate innovation efforts. We use the application year of patents, and not the patent granting date, as it better captures the date when innovators are in a position to incorporate technologies into products.

creases monotonically over the subsequent five years. After five years, the effect translates into a decrease of 47,813 tonnes per year (446,858 $\times$ 10.84%) of CO_2 and 6.19 tonnes per million dollars output (49.55 $\times$ 12.38%), respectively.

In Panel B, we look at Scope 2 emissions. We note that the hypothesis regarding Scope 2 emissions is less clear cut, due to substitution effects. For instance, if climate patents induce electrification, such as the replacement of fuel-powered with electric cars, customers' Scope 1 emissions decrease while their Scope 2 emissions increase. Nonetheless, our findings in Panel B closely match those for Scope 1 emissions. A one-standard deviation increase in the supplier's climate patent ratio is linked to a decrease of 5.85% in total emissions and of 6.22% in emission intensity (Scope 2).

Notably, Panel A and Panel B also show that there is no significant reduction in CO_2 emissions when the number of general patents granted to a supplier increases, indicating that the impact is specific to climate-related technologies. Moreover, the coefficients of the Customer's Climate Patent Ratio are all insignificant, indicating that the customer's climate technology has no impact on its own carbon emissions, confirming Bolton et al. (2023).

We find similar results when using the number of climate patents instead of the climate patent ratio, as shown in Table A3 in the Online Appendix. In addition, when we construct the climate patent ratio using the past three years' patent stock of suppliers, the outcome is similar, shown in Table A4.[21]

In theory, it should be possible to measure customer emissions by the downstream Scope 3 emissions reported by the supplier firm. Scope 3 emissions contain all indirect emissions (not included in Scope 2) that occur in the value chain of the reporting company, including both upstream and downstream emissions. Thus, we extend the analysis and look at innovators' downstream Scope 3 emissions in Table A5. We find no significant effect of climate patents related to product innovations. This finding confirms the result of Bolton et al. (2023) who also look at downstream Scope 3 emissions of innovators in their sample and find no effect. One possible reason is that Scope 3 emission data are unreliable since they are strongly downwards biased: for example, Klaaßen and Stoll (2021) find that reported Scope 3 data in the tech sector omit half of actual Scope 3 emissions.

[21]A possible concern is that suppliers with high climate patent ratios might be small innovators (e.g., if a firm has only one patent and that patent is climate-related, the climate patent ratio is 1). However, this concern does not appear to be important in our data: when we restrict our sample to firms with a climate patent ratio greater than 0.10, we observe that these firms filed an average of 19.12 climate patents. Also, the pairwise correlation between the climate patent ratio and the number of general patents is very low (0.02).

3.2 Extensions: Sample Size, Heterogeneity, and Process vs. Product Innovation

In this section, we discuss extensions of our baseline model, including the supply chain sample, heterogeneity analyses, and the distinction between process and product patents.

In the preceding section, we use a weighting method for multiple suppliers based on their relative sales to the customer firm. Since we lose approximately 90% of the observations due to missing supplier-customer pair sales data, our first extension is to consider the full supplier-customer sample. Since specific supplier-to-customer sales data are missing for most pairs, we follow Kale and Shahrur (2007) and deploy an alternative weighting approach that uses suppliers' firm-level sales data (from Compustat). Our estimates are presented in Table 4. Panel A illustrates that while the coefficients remain negative and statistically significant, the impact appears notably weaker compared to the findings in Table 3, especially noticeable in the fourth and fifth years. This suggests, unsurprisingly, that the emission impact is highest for the strongest supply chain relationships, those exceeding the mandatory reporting threshold of 10% of sales that constitute the overwhelming majority of supply-chain links where sales data are reported. Not without reason, these relationships are often categorized as dependent suppliers, reliant on a customer for a substantial portion of their revenues, in the literature (Intintoli, Serfling, and Shaikh, 2017).

In Panel B of Table 4, we further add the interaction between the supplier's climate patent ratio and the initial level of the customer's GHG emissions measured in year t. The interaction term is significantly negative (when we measure initial emissions in terms of intensity), indicating that customers with initially high emissions are more likely to benefit from their suppliers' climate innovations. While not being a silver bullet for high-emission firms, climate technology developed in the upstream supply chain is nevertheless an important tool when reducing their GHG emissions.

In Panel C of Table 4, we distinguish between climate product patents and climate process patents. Process patents propose new methods of producing an existing good, while product patents invent new products or improve existing one (Bena and Simintzi, 2022). We expect a much stronger effect on customer emissions for product innovations since with these patents, decarbonization technologies are embedded in final products and carbon emissions reductions should accrue for customers. The findings in Panel C confirm this hypothesis. Conversely, process patents are more likely to lead to a reduction of CO_2 emissions at the innovator firm (in unreported regressions, we find a stronger effect of process patents compared with product patents on innovator emissions.)

To conclude, these extensions confirm that there is a strong and robust correlation between suppliers' efforts on climate innovation and customers' capacity to reduce GHG emissions.

3.3 Technology Areas and Directed Technical Change

We next explore the areas and directions of climate innovation that generate the largest impact in terms of emission reductions. We do so with two separate investigations: we first consider which technology areas have the largest emission impact, and then explore whether directed technical change, and in particular the distinction between "green" and "grey" (or hybrid, energy-augmenting) technologies matters (Aghion et al., 2016).

In Table 4, we examine the differences between technology sectors, using the Y02 subcategories. Climate patents in renewable energy and energy efficiency (Y02E), building technology (Y02B), and transportation (Y02T) exhibit the strongest impact, again progressively growing over a five-year time frame. These three patent categories encompass activities with disproportionately high carbon emissions but also substantial climate patenting activity. This outcome is in line with our finding that emission reductions are more pronounced for firms with high emission intensity and with the expectation that these sectors hold the greatest potential for accelerated decarbonization (IEA, 2021). In contrast, we observe a comparatively weaker and less consistent impact of information and communication technologies (Y02D), even though climate patenting activity there is elevated. For carbon capture and storage (Y02C), caution is warranted when interpreting the results since the patent sample is notably small and concentrated. Finally, and somewhat unexpectedly, our analysis reveals no discernible effect for the production of goods (Y02P).

Next, we consider the role of the direction of technical change, first emphasized in the context of climate innovation by Aghion et al. (2016). We classify all climate patents into two categories, following Aghion et al. (2016): (i) "pure green" patents, that include technologies related to renewable energies (and their application) and to carbon capture; and (ii) "grey/hybrid" patents encompassing energy efficiency improvements that will mostly reduce the use and hence CO_2 emissions of fossil fuels. We re-estimate our baseline regressions separately for each of these two categories. The results, reported in Table A6, show that the strongest emission reductions can be imputed on "green" technologies. While perhaps somewhat surprising from the vantage point that energy-augmenting technologies are the low-hanging fruit in a world still dominated by the combustion of fossil energies, this finding bolsters the view that climate innovation is highly relevant for complete energy transition scenarios towards net zero emissions.

3.4 Stable Supply Chains and Exogenous Variation in Supplier Climate Patents

There are obviously endogeneity issues that we need to address. For example, it is possible that firms with a more ambitious climate agenda are more likely to select suppliers with a more pronounced climate innovation effort, producing a misleading association even when the supplier's climate patents do not causally contribute to the customer's CO_2 reduction. In a first pass to address specifically such concerns about selection effects between customers and suppliers, we investigate the change in emissions in a panel of *stable* supplier-customer relationships that exist prior to the climate patent applications. We use a supplier $\times$ customer $\times$ year sample where each observation represents a specific supplier-customer pair in a given year t, similar to Schiller (2018). We include supply chain relationships with both missing and non-missing sales in this analysis.

The regression results, presented in Panel A of Table 5, use the customer's forward-looking Scope 1 CO_2 emissions as the dependent variable and the supplier's climate patent ratio as the primary explanatory variable within a given supplier-customer pair. Importantly, we include supplier-customer pair fixed effects to account for the specific dynamics of each relationship and focus solely on within-pair variation. By doing so, we aim to address concerns about selection effects. The regression results show that for stable supplier-customer pairs, the customers' CO_2 emissions respond to suppliers' newly granted climate patents. The coefficients in Panel A are significantly negative, indicating a negative relationship.[22] However, the magnitudes of the coefficients are smaller than those in Table 3, because we treat each supplier-customer relationship equally, disregarding the varying importance of different suppliers to a specific customer. We obtain similar but weaker results for Scope 2 emissions in Panel B of Table 5, implying that a substitution between Scope 1 and 2 is possible.

[22] Coefficients are standardized and multiplied by 100 for readability.

But we need to push our empirical strategy to address endogeneity issues further. The analysis of stable supply chain relationships does not fully eliminate these concerns. It is possible that our findings may suffer from simultaneity bias, in particular the idea that customers may simultaneously undertake efforts to reduce emissions and lean on their suppliers to help this effort with new products that enable decarbonization, with no or a weak causal link between these two efforts.[23] Thus, looking at the panel of stable supplier-customer pairs is not sufficient to address all possible endogeneity concerns. Therefore, to establish a causal link between upstream climate patents and downstream emission reductions, we need to look for sources of exogenous variation in suppliers' creation of new climate patents that are orthogonal to customer decisions and characteristics. We do so with two independent identification strategies, based on R&D tax credits and examiner busyness.

Our first identification approach uses US state-level R&D tax credit changes as instrumental variable. Such R&D tax credit reforms are adopted by individual states to offer incentives to firms to invest in innovation, and their staggered nature has been used to show that they to generate significant increases in the quantity and quality of patents (Wilson, 2009; Mukherjee, Singh, and Žaldokas, 2017; Dechezleprêtre, Einiö, Martin, Nguyen, and Van Reenen, 2023). Our identification assumption is that, conditional on firm-level controls and fixed effects, changes in state-level R&D tax credits affect customer emissions only through their impact on supplier climate innovation. Therefore, we intentionally use general R&D tax credits (and not credits targeting green R&D) because green R&D tax credits might depend on state-level environmental performance (and green R&D tax credits are also rare). By using general tax credits, which are not specifically targeting green innovation, we avoid potential confounding factors related to environmental performance or spillover effects that might occur if the credit were green-specific.[24] In addition, to further strengthen our identification, we require that customers are located in a different state than the suppliers affected by state R&D tax credits. The data on R&D tax credits come from the Panel Database on Incentives and Taxes (PDIT).

In Table 6, we repeat the analysis of Table 5 using the state R&D tax credit programs as

[23]Note that this possibility does not refute our premise that climate patents causally contribute to customers' CO_2 emission reductions, since our premise does not require us to identify whether the work on climate patents is primarily initiated by suppliers or by customers (trying to do so would be a daunting task).

[24]Since general R&D tax credits are not aimed at green innovation, any innovation effect of the tax credit should predominantly affect patenting generally across all technology areas, rather than specifically climate-related or environmental innovation. This helps strengthen the argument that the instrument does not affect customer emissions via any direct green preference channel.

instruments and limiting the sample to stable supplier-customer pairs (supplier × customer × year level).[25] In Panel A, we confirm that, in the first stage, state tax credits increase both climate patents and general patents inventions by 2.3% and 1.5%, respectively.[26] Concerns that our instrument may be weak seem not to be warranted, as the strong F-statistics indicate. In Table A11 (Online Appendix), we further confirm that state-level R&D tax credits increase patents in a more regular firm × year sample. In Panel B (the second stage), a supplier's climate patents driven by government R&D tax credits lead to 1.1% emission reductions for its customer firms. We find that results for Scope 1 are generally stronger than those for Scope 2, again consistent with Table 5.

In our second identification approach, we focus on the quality of climate patents. To do so, we look for a different source of exogenous variation that generates heterogeneity in the quality and impact of patents. We follow Shu et al. (2022) who argue that when a patent examiner reviewing a given patent application is very busy with other patent applications, she will spend less time on the focal patent, resulting in lower quality of the patent, conditional on being granted. They show that patent examiner busyness is a powerful predictor of patent quality, as measured by forward patent citations. In the climate patent context, examiner busyness is measured as the total number of decisions (including patent allowance, non-final rejections, and final rejections) made by the examiner who evaluated the focal climate patent (excluding decisions involving focal climate patent) in the year it was allowed.[27]

We believe that the climate patent examiner busyness measure is plausibly exogenous and orthogonal to the customer firm's specific preferences or characteristics because it is essentially determined by, one, the patent application flow in the USPTO technology art unit and, two, the working schedule of the assigned examiner's colleagues. Table A7 applies patent examiner busyness to climate patents in our supplier-customer sample. In Panel A, the first stage, we show that the examiner busyness measure is negatively associated with patent citations. Panels B and C, the second stage, demonstrate that when a supplier's climate patent is of lower quality (i.e., higher

[25] The value of the credit varies from state to state depending on the credit rate, how the base amount is calculated, and whether the credit itself may be "recaptured" (in the sense that it is considered taxable income) (Wilson, 2009). PDIT calculates state-level tax credit value as percentage of the average value-added by firms in a given industry within a given state. We use the average tax credit value across all industries in a given state as our main instrumental variable.

[26] Our instrumental variable and dependent variables in Panel A are standardized (S.D. equals 1) and coefficients multiplied by 100.

[27] Patent allowance is an email notifying the patent applicant that the patent is now approved. Patent allowance occurs on average 6 months before the official granting date.

examiner busyness), it has a significantly weaker effect on customer carbon emission reductions.

3.5 Emissions of Customers of Customers

In an additional analysis, we look at indirect emission reductions that accrue at the customers of customers. The idea is that emission savings may trickle down further in supply chain networks in multiple ways, linked to the nature of the products (for example, climate innovations of parts manufacturers yield savings mostly for customers of customers) or various spillover effects. Looking at the customers of customers also removes endogeneity concerns by one layer: while direct customers may not be randomly exposed to the climate patents of their n+1 suppliers (hence our need for instrumental variables), for the customers of these customers, the same climate patents are arguably mostly exogenous shocks of their n+2-suppliers.

To implement this idea, we first identify all supply chain relationships in the next layer, that is of customers of the customers in our sample, and then look at the emission effects of the climate patents of their n+2 suppliers in the same format as we did in Table 5. Our results in Table A8 show significant and increasing emission reductions for the first three years after the n+2 supplier's climate patents for Scope 1 emissions. The effects are considerably weaker than for direct customers (and insignificant for Scope 2 emissions) but this is as expected, given the indirect nature of the n+2 supply chain relationship.

4 Extensive Margin: Emissions of New Customers

We turn to the extensive margin channel. We identify new supply chain links and examine the associated emission reduction effects for newly acquired customers. We then address endogeneity concerns by exploiting exogenous shocks to supplier-customer networks arising from merger bids.

4.1 Customers' Carbon Emissions: New and Old Suppliers

We study the emission effects for new customers in a set-up that directly compares the effects for new and long-standing supply chain relationships. Table 7 does so by analyzing changes in future customer carbon emissions following new climate patent invention of new and of long-standing (old) suppliers. The key variable of interest is the dummy variable "I[New Supplier with Climate Patents]," which is equal to 1 if the customer has a new supplier with a climate patent ratio greater than 0.2, and 0 otherwise. For the sake of comparison, we define a symmetric dummy variable for old suppliers, "I[Old Supplier with Climate Patents]," which is equal to 1 if the firm has long-standing suppliers (relationships starting five years ago) with a climate patent ratio greater than 0.2; this variable can be viewed as a discrete version of the continuous "Supplier's Climate Patent Ratio" used earlier (Table 3 to Table 5).[28] The climate patent ratio is calculated using the supplier's patents with applications filed in years $t-2$, $t-1$, and t. Panels A and B of Table 7 present the results for Scope 1 and Scope 2 emissions, respectively. Panel A shows that the reduction impact for firms with a new supplier is approximately 11% after five years. Thus, the measured emission reduction impact is significantly larger than for customer firms in existing supply chain relationships, where we observe a reduction of 2% to 5% in $t+5$. Similar results are observed for Scope 2 emissions. Overall, climate innovation is effective in reducing CO_2 emissions for both new and existing customers, but the effect is markedly more pronounced for new customers, and particularly when it comes to direct (Scope 1) emissions.

A key empirical challenge is the potential endogeneity in customers' move to switch suppliers, i.e. the endogeneity of "I[New Supplier with Climate Patents]." Firms with more ambitious decarbonization goals may have a systematically higher propensity to form *new relationships* with suppliers that offer more climate innovation, confounding the estimated effects. Our prior identification strategies relating to shocks in patent creation — based on state-level R&D tax incentives and patent examiner busyness — cannot address this concern about the selection of *new* suppliers. To mitigate this issue, the following section introduces a novel identification strategy that isolates exogenous variation in supply chain formation.

4.2 Supplier Mergers: Exogenous Shocks to Climate Innovation

Our identification strategy starts from the observation that when a supplier is acquired in a successful merger, it disappears as an independent firm and its supplier–customer relationships also end. However, while the customer can no longer contract with its now-defunct supplier, the

[28] Our results are qualitatively similar when using a threshold equal to 0.1 or 0.3.

production operations of the former supplier are typically continued by the acquirer firm and the customer will frequently just carry on with its existing supply chain logistics, now transferred to the acquirer. Thus, our approach is based on the identifying assumption of inertia in supply chains, driven by switching costs, organizational convenience, lack of attention or other frictions. We find plausible empirical support for this pattern in our merger data.[29] Crucially, the acquirer becomes, from the customer's perspective, an exogenously assigned new supplier, with possibly a different climate innovation potential or record. Importantly, this form of supply chain transitions is plausibly orthogonal to the customer's decarbonization agenda, and therefore offers a source of exogenous variation in a customer's change of suppliers. Moreover, to exclude any possible confounding effects related to the former supplier becoming an acquisition target, our identification strategy only considers suppliers with merger bids: suppliers with successful merger bids (who cease to exist) are the treated sample, whereas suppliers with failed merger bids the control sample.

Figure 2 illustrates our identification strategy. Supplier S serves customer C, and supplier S' serves customer C'. Both S and S' are targets in merger deals; S is successfully acquired by firm A, while the deal involving S' fails. Following the acquisition, customer C then switches from sourcing inputs from S to sourcing from the acquirer, A. We further identify that A holds a substantial fraction of climate-related patents *prior to* the merger. We interpret the formation of this new supply chain link, with a climate innovator as new supplier, as plausibly exogenous. In our regressions, we implement a difference-in-differences specification in which customer C belongs to the treated group and customer C' to the control group. The post-merger period is defined as the years following the effective completion or withdrawal date of the merger bid.

Table 8, Panel A, reports summary statistics for the construction of the treatment and control groups. Restricting the sample to transactions in which both the acquirer and the target are publicly listed in the CRSP-Compustat database, we find 3,834 successful and 639 failed merger deals from the SDC database. We limit the sample to merger bids, as targets typically cease to operate independently following such transactions.[30]

Among 73,477 unique supplier–customer relationships in our sample, 2,385 involve suppliers that

[29] The proportion of customers retaining the acquirer as supplier, a bit less than a quarter in our data, is likely an undercount of the underlying inertia as the data drop cases where customers reduce their exposure to the acquirer below the reporting threshold or face a demerger of the relevant supplier activities.

[30] This stands in contrast to acquisitions of majority interests, where targets may continue to operate as standalone entities.

are targets of merger bids. Figure A1 in the Online Appendix plots the frequency of supply chain terminations in a ten-year window around the completion of a merger bid of the supplier firm. It shows that supply chain termination is clearly clustered at this merger completion event, with 1,797 supply chain relationships being terminated in the two-year window of the merger completion year or the preceding year. Panel A of Table 8 (Figure A2) further shows that in 398 of these 1,797 cases, the customer switches to the acquirer as the new supplier in the year of merger completion and the following 2 years. We then restrict our variable of interest to cases in which the acquirer is also a climate innovator prior to the merger announcement (defined as having more than 5% of patents classified as climate-related). These successive filters yield a sample of 33 supplier–customer relationships that are our treated group. The control group is constructed analogously, using failed mergers.

Panel B of Table 8 and Figure 3 present the difference-in-differences estimates for the emission impact of these merger-induced supply chain reconfigurations. We find that climate innovation by the new supplier (the acquirer) leads to a statistically and economically significant reduction in carbon emissions of the customer firm.

Although the merger is exogenous to customers, customers can still decide whether to retain the acquirer as a substitute supplier or to switch to other suppliers. This decision may correlate with the customer's future decarbonization plans or the acquirer's climate patent activity. We address this concern by exploring whether the customer's choice to retain the acquirer as supplier is explained by the acquirer's climate innovation (climate patent ratio in the three years prior to the merger), the customer's carbon emissions or change in carbon emissions, or the interaction between these variables. As we show in Table A12, none of these variables has explanatory power, indicating that our supply chain disruption is exogenous and not driven by customers' willingness to decarbonize and supporting the validity of our difference-in-differences setup.

5 The Mechanisms of New Customer Acquisition

Having established that climate innovation reduces customer CO_2 emissions (Sections 3 and 4), we now examine how it triggers the reconfiguration of supply chain networks. Specifically, we analyze the mechanisms through which climate innovation enables suppliers to attract new customers and identify which types of customers are most responsive to climate technologies. Importantly, throughout this section, our findings are conditional on suppliers having already produced new climate patents. As this innovation has real environmental benefits (as we have shown), customer sorting, or selection based on this attribute, is an economically meaningful amplification channel. Thus, the preference-based matching behavior that we describe is fully in line with the causal interpretation of the emission reduction benefits established earlier. It broadens the perspective on the scale and scope of these benefits by showing their reach beyond existing supply chain networks.

Our findings so far establish that innovation matters for emission reductions; this part shows that customers recognize and act upon this. From an economic perspective, this two-way interaction—innovation causes impact, and impact drives sorting—is realistic and policy-relevant.

We begin with the demand side, asking whether customer firms exhibit a preference for suppliers with stronger climate innovation (Section 5.1).[31] We then turn to the supply side, exploring which types of new customers climate-innovating suppliers are most likely able to attract (Section 5.2). Section 5.3 documents that the effects of new supply chain formation are stronger after 2010. Section 5.4 examines the channels of successful new customer acquisitions, while Section 5.5 investigates which patents matter most for business stealing. Section 5.6 addresses causality, and the final subsection studies the implications for operating performance.

5.1 Customers' Choice of New Suppliers: Discrete Choice Model

We first ask whether climate innovation plays a role in customers' choice of new suppliers. To investigate this question, we develop a discrete choice model (McFadden, 1974) of customers' selection among a set of potential suppliers and explore the role of climate innovation in this choice.[32]

[31] In fact, it is not a foregone conclusion that climate innovation will facilitate business expansion. Suppliers are likely to charge a premium for their climate innovation. Fowlie (2010) documents that reducing GHG emissions is costly and not obviously profit-enhancing which may stifle demand. However, the literature provides a number of possible explanations why the net effect may result in business expansion. First, as climate change garners more attention, there is an increase in consumer willingness-to-pay for greener products and in firms' willingness to favor suppliers with high ESG ratings (Schiller, 2018). Second, the growing interest in sustainable investments (Hartzmark and Sussman, 2019; Ardia et al., 2022) and attention of financial markets to carbon transition risk results in a lower cost of capital for firms with lower emissions (Chava, 2014; Bolton and Kacperczyk, 2022; Pástor, Stambaugh, and Taylor, 2022). Thus, customers should be increasingly receptive to the idea of adopting new climate technology and paying a premium for it.

[32] In principle, the establishment of supplier-customer relationships involves a two-sided matching process. However, customer firms tend to be several times larger than their suppliers on average (Schiller, 2018) and

For each customer firm in a given year where it has at least one recorded supply chain link, we create a choice set of possible suppliers that, in addition to the actual supplier, includes potential suppliers that offer similar products to the actual supplier but are not currently suppliers and that we identify using Hoberg and Phillips (2016)'s text-based product description measures. The baseline regression uses the model:

$$I(\text{Select})_{c,s,t} = \beta_1 X_{s,t-1} + \beta_2 X_{c,t} + \beta_3 X_{s,t-1} \times X_{c,t} + \chi_c + \varepsilon_{c,s,t} \tag{3}$$

where the dependent variable $I(\text{Select})_{c,s,t}$ is a dummy that equals one if the customer firm c selects the supplier s to establish the supply chain relationship in year t and the sample is at the customer $\times$ potential supplier $\times$ year-level, allowing us to control for the firm characteristics of both suppliers and customers, as well as their interactions.[33]

Table 9 reports the findings. In column (1), the coefficient of the supplier's climate patent ratio is positive and highly significant, implying that customers prefer suppliers with climate innovations. Specifically, an increase in the interquartile range of the climate patent ratio is associated with a 12% increase in the probability of selecting that supplier. The effect is also strongly positive for general patents. This is a necessary control variable in our context to make sure that climate patents are not simply picking up a reaction to general supplier innovation, and the strongly significant and positive coefficient also underlines the validity of our methodology. To the best of our knowledge, this empirical approach is novel in the innovation and in the supply chain literature and we are the first to document such a business expansion effect for supplier patents in general.

Column (2) of Table 9 breaks the sample period into two sub-periods, before and after 2010. The regression reveals that the effect, while seemingly significant for the full sample, is really explained only by climate patents with date starting in 2010: only the coefficient on the supplier's *climate patent ratio* $\times I(\text{Post 2010})$ is significant, i.e. customer firms start to express a positive preference for climate innovation only after 2010. In contrast, there is no significant difference between the coefficients of supplier's *number of general patents* $\times I(\text{Post 2010})$ and supplier's *number*

hence to have more bargaining power.

[33] Our model differs from a standard discrete choice model in two ways. First, a typical customer in our regression can choose multiple suppliers in the same fiscal year whereas a textbook discrete choice model assumes exclusivity among alternatives. Second, since we introduce complex two-way and three-way interactions, we use a linear probability model instead of conditional logit that would make the interaction terms much harder to interpret (Ai and Norton, 2003).

of general patents $\times I$(Before 2010). This means that there is a structural jump in the importance of climate innovation around 2010, but not for general (non-climate) patents. This structural break is important for our analysis and we explore it in more detail in Subsection 5.3.

We next explore the heterogeneous impact of climate innovations on different types of new customers. The discrete choice model allows us to control for the firm characteristics of both suppliers and customers, as well as their interactions. Table 9 shows in column (3) that the interaction term between the supplier's climate patent ratio and the customer's environmental score (E-score) is positive and significant, indicating that customer firms with a high environmental score have a stronger preference for the supplier's climate technology. In contrast, the interaction term between the supplier's number of non-climate patents and the customer's E-score is insignificant. Column (4) conducts placebo tests by adding the interaction terms between the climate patent ratio and the social score and governance score (the other subscores in their ESG score). It shows that the stronger preference is not true for customers with high governance or social scores. Column (5) interacts with a post-2010 dummy and shows that the preference for suppliers with new climate technology by customers with a high E-score exists only after 2010. By contrast, including customer size does not alter the results (column (6)). A high environmental score is considered as a proxy for firms' preferences regarding environmental and climate change issues,[34] implying a greater willingness-to-pay for climate innovation.[35]

In columns (7) and (8) of Table 9, customers with high emissions (either measured by total emissions or by emission intensity) are more likely to choose climate-innovative suppliers,[36] and again, significantly so only after 2010, not before. While it may appear paradoxical that high-emission firms exhibit a stronger propensity to select suppliers with climate technology advances, we note that, first, high-emission firms are not necessarily those with low environmental scores. Table 2, Panel D, shows a very low pairwise correlation between the components of the environmental score and CO_2 emissions.[37] Second, firms with large carbon footprints have reasons to be sensitive

[34]Such a preference, initially discussed by Bénabou and Tirole (2010) and further explored in the growing literature on CSR (or ESG) preferences, can be attributed to various motives, including a belief among decision-makers in the principle of "doing well by doing good" (Baron, 2001), personal preferences of CEOs and board members, or pressure from shareholders and other stakeholders.

[35]See, for example, https://www.mckinsey.com/capabilities/sustainability/our-insights/how-much-will-consumers-pay-to-go-green.

[36]We add the interaction between customer firm size and supplier climate patent ratio since firm size is highly correlated with CO_2 emissions.

[37]To understand the low correlation, similar to findings e.g. in Boffo, Marshall, and Patalano (2020), it

to climate innovation because of the potential larger benefits of reducing emissions,[38] and finally, high-emission firms have been shown to be active climate innovators themselves (Cohen et al., 2021).

5.2 Innovators' Capacity to Acquire New Business Customers

In our second pass on the questions regarding knowledge diffusion and new customers, we approach the issue from the suppliers' perspective and their capacity to attract new customers. We construct our sample of potential suppliers following Section 2.4 and run the following regression,

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{\text{Year}=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t \Big) + \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (4)$$

The dependent variable "Num_New_Customer_Firms" counts how many *new business customers* start to purchase products or services from firm i in year t.[39] From now on, we calculate the climate patent ratio using the patent granting year, as the granting date better reveals a signaling effect for new customers. We lag the climate patent ratio by one year and interact it with $\Big\{ I(\text{Year})_t \Big\}_{\text{Year}=2005}^{2021}$, a set of dummies equal to 1 in year t, where $t = 2005, 2006, \cdots, 2021$. The interaction helps to study the possibly time-varying effect of climate innovation on the acquisition of new customers. Moreover, we control the number of general patents measured in year t-1.[40] We plot the coefficients of $\beta_{1,\text{Year}}$ as well as their confidence intervals at the 90% level in Figure 4.

Figure 4 shows that the coefficients of $\beta_{1,\text{Year}}$ are positive and significant only after 2010, with magnitudes ranging from 0.1 to 0.3. An increase in the interquartile range of the climate patent ratio is associated with a 7.35% to 22.06% increase in the number of new business customers. In contrast, the coefficients before 2010 are not significantly different from zero. In the Online Appendix (Figure

is useful to note that environmental scores are calculated relative to each industry, while CO_2 emissions are not; also, environmental scores typically encompass more dimensions besides GHG emissions.

[38] High-emission firms tend to be exposed to the strongest pressure from climate-conscious institutional investors (Atta-Darkua et al., 2022) and to have a higher cost of capital (Bolton and Kacperczyk, 2021b).

[39] A new customer is defined as a customer that has never purchased products from firm i before and starts buying in year t. We apply the $\ln(1 + x)$ transformation to our dependent variable, and we use Poisson regressions without this transformation as a robustness check.

[40] $\mathbf{X}_{i,t}$ includes firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth and PPE (this follows Bolton et al. (2023)). Standard errors are clustered at the firm level.

A3), we conduct robustness checks using Poisson regression and find similar results.[41] In Figure A4, calculating the climate patent ratio using the patent application date yields results similar to those based on the granting date, but with greater fluctuations in the coefficients post-2010.

We also investigate whether the acquisition of new customers is not just a consequence of increased customer turnover following climate innovation. To do so, we consider the choices of climate innovators' existing customers, and specifically whether they remain loyal or switch to other suppliers, possibly as a result of higher costs or unwanted changes in technology. In Panel D of Table 10, we regress the number of existing customers who stop buying products from a given climate innovator, before and after 2010. It shows that existing customers do not tend to defect from climate innovators, as all coefficients in the three columns are far from significant. In summary, climate patents help suppliers attract new customers, but do not drive away old customers. They appear to benefit from a net gain in their customer base.

5.3 Strong Customer Acquisition Effects After 2010

The results presented in this section show a strong structural break around 2010, with customer acquisition reacting strongly to climate innovation after that date. We are not alone in the literature in finding a stronger corporate response to climate-related announcements in the post-2010 period. The failure of the December 2009 Conference of the Parties (COP15) to produce a new global climate agreement had the effect of a shock that significantly raised public attention to climate change (Ardia et al., 2022), and papers on the market reactions to climate news typically find a similar structural break during 2010 and 2011. For example, Choi et al. (2022) show that the price valuation gap between high-emission firms and low-emission firms was close to zero before 2011 but significantly negative afterwards. Besides the failure of COP15 to produce a climate agreement, there are several concomitant developments that can explain heightened sensitivity to climate innovation news. Notably, the break is possibly related to the introduction of the "Y02/Y04S" scheme by the European Patent Office (EPO) and the USPTO which allowed to easily identify whether a given patent is climate-related. Previously, this information was scattered across many IPC and CPC

[41] In the remaining analysis, we use the ln(1+x) transformation instead of Poisson regressions because Poisson regressions impose strong assumptions on the distribution of error terms and are subject to issues of under- or over-dispersion (Wooldridge, 2010); and our empirical model uses many interaction terms for which the coefficients are difficult to interpret in non-linear regressions (Shang, Nesson, and Fan, 2018).

categories, and was difficult to identify for non-specialists (Angelucci et al., 2018). In addition, there were other simultaneous initiatives to enhance the impact and visibility of climate patents. For example, in December 2009, the USPTO implemented the Green Technology Pilot Program, which allows patent applications related to energy conservation, development of renewable energy resources, and reduction of greenhouse gas emissions and environmental quality to be advanced out of order for examination and to get accelerated review. These schemes, including the "Y02" scheme, helped stakeholders including customer firms to quickly screen for climate-relevant patents and they could also be exploited in the marketing efforts of innovating firms.

To discern the role of the 2010 break on the perception of climate patents, we plot the annual median market value of climate and non-climate patents separately in Figure 5.[42] We follow Kogan et al. (2017)'s method for estimating the market value of a given patent, where they estimate the economic value of patent j as the product of the estimate of the stock return due to the value of the patent times the market capitalization of the firm that is issued patent j on the day prior to the announcement of the patent issuance.[43] For climate patents, we only include Y02E (renewable energy and energy efficiency) and Y02C (carbon capture and storage) because the original Y02 scheme in 2010 only included these two categories (Veefkind, Hurtado-Albir, Angelucci, Karachalios, and Thumm, 2012; Calel, 2020). The figure shows a large jump between 2010 and 2011 in the value of climate patents. By contrast, there is no comparable jump for non-climate patents. This implies that after 2010, climate patents are able to attract not only the attention of customers but also of financial markets. Interestingly, we do not find a similar 2010 jump for other Y02 categories that did not exist in 2010 and that were only backfilled several years later, showing that the relatively prompt delivery of the "Y02" tag was probably important.

5.4 Channels of Successful New Customer Acquisitions

Next, we explore the transmission channels that allow climate innovators to attract new customers, exploiting the heterogeneity of customer firms and asking what types of customer respond significantly and most strongly to new climate technology in their supply chain choices. Table 10

[42]We plot the median instead of the mean to avoid the effects of outliers.

[43]We use data on the market value of patents from Kogan et al. (2017).

addresses this question by estimating the following regression,

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \beta_1 \text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Post 2010})_{i,t} +$$
$$\beta_2 \text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Before 2010})_{i,t} + \beta_3 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_4 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \tag{5}$$

In columns (1) and (4) in Panel A of Table 10, the dependent variable is the number of new customers attracted by firm i (the same as in Section 5.2). In addition, we perform a median split of the sample of all new customers in a given year using their environmental scores (see Section 2.3). In columns (2) and (5) ((3) and (6)), the dependent variable includes only newly acquired customers with environmental scores above (below) the sample median of that year. shows that The summary statistics are very similar between these two subsamples (Table 2, Panel B). The variable of interest is the climate patent ratio (measured in year t-1), interacted with two dummies for the periods before and after 2010 (see Section 5.3). Finally, columns (1) – (3) add industry × year F.E., while we control for firm F.E. in columns (4) – (6).

Columns (1) and (4) of Panel A demonstrate that climate innovation has been instrumental in attracting new business customers post-2010, but not earlier (echoing the findings in Figure 4). Moreover, columns (2) and (5) show that the regression coefficients are positive and significant for new customer firms with high environmental scores, but not with low environmental scores (columns (3) and (6)). These findings indicate that climate technology is particularly effective in attracting new customers prioritizing environmental performance, in line with our earlier findings from the discrete choice model presented in Table 9, column (3).

In Panel B of Table 10, we conduct a similar sample split, using a measure of customer's active environmental engagement in their supply chain management. The variable used for the median split, constructed by LSEG (formerly Refinitiv), indicates whether a customer firm considers environmental impacts when selecting its suppliers.[44] As illustrated by the coefficients in Panel B, a supplier's climate innovation significantly attracts new customer firms committed to environmental supply chain management, but this effect is observed only after 2010.

In Panel C of Table 10, we undertake another sample split based on the annual CO_2 emissions of customers, using the sum of Scope 1 and Scope 2 emissions (in tons). We do not make any within-

[44] We exclude customers for whom the measure of ESG supply chain management is missing.

industry adjustments for CO_2 emissions, following the perspective in Choi et al. (2022) and Bolton and Kacperczyk (2022) that raw and total carbon emissions more accurately capture a firm's carbon transition risk. Echoing our findings in Table 9, we find in Panel C that new customers attracted by a supplier's climate technology are those with high CO_2 emissions. Conversely, firms with relatively low emissions are less likely to purchase products from climate innovation suppliers, as indicated by the negative coefficients of the climate patent ratio $\times I$(Post 2010) in columns (3) and (6).

In a further robustness test, we check whether the acquisition of new customers is facilitated when switching costs are low. We split the customer sample using two widely used proxies for switching costs, customer size and the homogeneity (product similarity) of customers' supplier network. As expected, Table A10 shows that suppliers more easily succeed in attracting customers with lower switching costs (large customers and customers with a homogeneous supplier network).

5.5 New Customers, Patent Quality, and Product Relatedness

In this section, we look for corroborating evidence by asking whether more valuable climate patents have a stronger pull effect on attracting new customers. We explore the heterogeneous impact by differentiating climate patents according to various measures of their usefulness. First, we differentiate climate innovations by patent quality (Cohen, 2010). Patent citations, the traditional measure of patent quality (Jaffe and Trajtenberg, 2002), are problematic in the context of climate patents that overwhelmingly are fairly recent, in view of the long lag in patent citations (Lerner and Seru, 2021). Therefore, we use Kogan et al. (2017)'s measure of the market value of patents as proxy for patent quality.[45] In Panel A of Table A9, we split our climate patent ratio into two subcategories, with Climate Patent Ratio (High Value) counting the number of new climate patents (filed by firm i in year t and ultimately granted) with a market value above the median of all climate patents in year t (and Climate Patent Ratio (Low Value) those below the median). The dependent variable in Table A9 is the number of new customers acquired by a given supplier. We distinguish new customers along the two dimensions considered before, high/low environmental score and high/low carbon emissions. The coefficients in Panel A of Table A9 show that the capacity of climate innovators to attract new customers is clearly driven by high-value climate patents.

[45] Kogan et al. (2017) estimate the market value of a patent as the observed stock return on its announcement day times the market capitalization of the patentee, and show the strong correlation of this measure with subsequent patent citations. Data on the market value of patents are from Kogan et al. (2017).

Second, we investigate the notion that the capacity to attract new customers depends not only on the intrinsic value of a patent (patent quality) but also on its usefulness for products and processes. Innovations are of little use for customers when the innovator does not embed them in products or shows customers how to deploy them. Patent value might be misleading in this regard; for example, Cohen, Gurun, and Kominers (2019) argue that many patents can be of great strategic value but of no production value to the patent holder. We proxy this idea by looking for a measure of the extent to which a given climate patent is related to the final products that the innovator sells to customers. Since the existing innovation literature offers little help in linking patents to the patentee's products, we construct our own measure, largely inspired by Kogan et al. (2021).

We use an advanced deep-learning method in natural language processing to compute the pairwise document similarity between a given patent text and the patent holder's product description. A higher similarity (technically, cosine similarity) is interpreted as implying that a given patent is more critical for the firm's core products. To obtain patent content, we follow Kogan et al. (2021) by using the title, abstract, and detailed description text of the patent. We obtain product descriptions from 10-K filings (Item 1. Business Description) following Hoberg and Phillips (2016). We then use the Stanford GloVe model (Global Vectors for Word Representation) to compute pairwise text similarity between climate patent text and product description text.[46] Figure 1 shows and discusses an example of our pairwise document similarity, for a patent granted to Western Digital with the Y02D tag.

Panel B of Table A9 reports our results. It shows that only climate patents that are highly correlated with the supplier's products attract new customers. The dependent variable is still the number of new customers acquired by a given supplier. We distinguish new customers along two dimensions: Environmental score and GHG emissions (Scope 1). We sort all climate patents into two groups by the median of product-patent cosine similarity. Climate Patent Ratio (Highly-Related) is equal to the number of new climate patents (filed by firm i in year t and ultimately granted) whose product-patent cosine similarity is higher than the annual median cosine similarity for all climate patents divided by the total number of general new patents filed by firm i in year t.

Panel C shows that new customers are primarily acquired in times of high public attention to climate change, indicated by the interaction of Climate Patent Ratio with the MCCC-index, a

[46] We include only nouns and use the TFIDF adjustments in our calculations. All details on the procedure to implement the Stanford GloVe model can be found in Kogan et al. (2021).

widely used index of the news coverage of climate change. This also highlights the importance of patent value since, as Ardia et al. (2022) show, the MCCC index is strongly correlated with the appreciation of corporate climate policies.

5.6 Identification: Random Variation in Patent Grants

The results in this section reveal many plausible mechanisms that facilitate customers' decision to establish new supply chain links in reaction to climate innovation, related to customer characteristics, patent value and quality, and heightened climate sensitivity in the post-2010 period. Endogeneity concerns are arguably less important in this context than in our study of emission effects. Still, we adopt an identification strategy to address any possible confounding effects in the relationship between climate innovation and the transmission channels of new customer acquisitions analyzed in Table 10. As our instrumental variable, we use random shocks in the leniency of patent examiners and hence in the probability of patent approvals that arise from the quasi-random assignment of lenient or tough patent examiners in most USPTO technology art units.[47]

Table 11 shows the results when we replicate the set-up of Table 10, using examiner leniency as an instrument to study an exogenous shock in the capacity to attract *new* customers.[48] Columns (1) and (2), the first-stage regressions, show a strong and positive predictive relationship with the climate patent ratio (the associated $F-$statistics are very high). In both panels A and B, we find exactly the relationships of Table 10: a strong effect on attracting new customers that is highly significant for new customers with high environmental scores and elevated emissions. These outcomes should alleviate concerns regarding omitted variable bias and bolster the case for a causal interpretation. Details of the identification strategy and the implementation of the patent examiner instrument are explained in Appendix A (Online Appendix). In unreported robustness tests, we address concerns about the randomness of the patent examiner instrument raised in the literature,

[47]The literature has demonstrated that some patent examiners are more lenient and grant patents more easily than other examiners in the same field of patent applications, for person-specific, idiosyncratic reasons and that in most USPTO technology art units, patent examiners are assigned to patent applications in a quasi-random fashion(Cockburn, Kortum, and Stern, 2002; Sampat and Williams, 2019)

[48]Our instrument is based on the identification assumption that for the acquisition of *new* customers, the intellectual property rights protection and the "certification" effect of the patent award matter, not just the underlying technology that is independent of its patent status. Patent protection prevents industry competitors from developing similar technology and new customers are not yet familiar with the supplier's technology (by contrast, in existing supply chain relationships with their often dense communication channels, the technology rather than the patent status should play a greater role).

including firms being strategic in their patent application claims to be allocated to more lenient art units with examiners, and find that they do not affect our results.

5.7 Operating Performance of Climate Innovators

We have shown that climate innovation helps suppliers to attract new customers, but does not lead to the departure of existing customers (Table 10). The resulting net gain in customers, as well as possible larger sales or profits because climate innovation may command a higher mark-up, can be expected to lead to sales growth and profit improvements. To explore this idea, Table 12 examines how climate innovation affects suppliers' operating performance. In column (1), the dependent variable is the natural logarithm of sales. Consistent with our intuition, the coefficient of the climate patent ratio (t-1) $\times I$(Post 2010) is positive and significant. Climate innovation is associated with sales growth, but only after 2010. In columns (2) and (3), we examine return on assets (ROA) and mark-up, respectively, where mark-up is defined as (total sales $-$ cost of goods sold)/(total sales). Interestingly, climate patent ratio (t-1) $\times I$(Post 2010) is positive (but not significant), but the coefficients of climate patent ratio (t-1) $\times I$(Before 2010) are negative and significant. Thus, there is indeed a significant improvement in sales and mark-ups after 2010, but the initial effect of climate patents on return on assets and mark-ups is negative (which is consistent with the findings by Bolton et al. (2023) that the climate patent ratio predicts declining market shares and profits). Our suggested interpretation is that prior to 2010, when the willingness-to-pay for climate mitigation was low, climate innovators were probably not able to pass on the cost of their innovation activity and their profitability deteriorated. After the structural break around 2010 (Section 5.3), they managed to obtain an adequate return on their climate innovation investment.

6 Conclusion

We study the impact of climate innovation on carbon emissions and business expansion, focusing on downstream supply chain networks. We show that climate-related product patents (but not process patents) allow customer firms in existing supply chain connections to reduce CO_2 emissions (intensive margin effect) and that emission cuts are magnified for high-emission firms and firms with stronger environmental concerns. We show that the emission reductions are even larger for new customers acquired after the climate patent applications (extensive margin effect). The effect is strongest for patents in energy production, transportation and buildings, and for "green" (as opposed to "grey") technology. Only the combined study of both channels allows a full appraisal of the carbon emission benefits of innovation. We provide multi-layered evidence that the association between climate patents and customer emissions reductions is causal: the effect is confirmed in panel regressions of longstanding supply chain relationships, and we deploy several identification strategies: state-level R&D tax and examiner busyness introduce exogenous variation in the production and quality of climate patents in the intensive margin channel, and successful versus failed mergers of suppliers provide an exogenous shock to the new supplier's propensity for climate innovation.

We also study the mechanisms that allow climate innovators to expand their business by adding new supply chain connections. We show that customer firms have a strong preference for suppliers that are climate innovators and that climate innovation allows suppliers to expand their customer base. The propensity to switch supply chain links to climate innovators is more pronounced for high-emission customer firms and firms with high environmental scores, for high-value patents and patents with a stronger footprint in the supplier's product portfolio, and it is amplified in the post-2010 period when attention to climate mitigation and the value of climate patents rise substantially.

The widely held view of innovation as an indispensable tool to mitigate climate change has led to numerous public policies, including subsidies and regulations, that aim to foster the development and adoption of new climate technologies. The climate benefits of such technology-related policies, however, are not firmly established. Against this background, we make two key contributions. First, we establish that climate innovation produces scalable carbon reduction benefits via supply chain propagation and that new customers amplify these benefits. Second, customers' revealed preference for new clean technologies and willingness to reconfigure supply chains provide market-based incentives for upstream innovation, complementing direct regulation. These insights inform the design of innovation policies and supply chain strategies in a decarbonizing economy.

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Figure 1. Patent-to-Product Relatedness for Climate Innovation

Patent Document ◄- ► **10-K Product Document**

Enhanced Queue Management For Power Control Of Data Storage Device

PATENT NUMBER	DOCUMENT ID	DATE PUBLISHED
9965206	US 9965206 B2	2018-05-08

CPC CURRENT

TYPE	CPC	DATE
CPCI	G 06 F 3/0676	2013-01-01
CPCI	G 06 F 3/0625	2013-01-01
CPCI	G 06 F 3/0659	2013-01-01
CPCI	G 06 F 3/0653	2013-01-01
CPCI	G 06 F 3/0673	2013-01-01
CPCA	Y 02 D 10/00	2018-01-01

ASSIGNEE INFORMATION

NAME	CITY	STATE	ZIP CODE	COUNTRY
Western Digital Technologies, Inc.	San Jose	CA	N/A	US

Abstract

Systems, methods, and firmware for power control of data storage devices are provided herein. In one example, a data storage device is presented. The data storage device includes a transaction queue configured to enqueue storage operations received over a host interface of the data storage device for storage and retrieval of data on storage media. The data storage device includes a storage controller configured to process a power/current target to establish a dequeue process for storage operations in the transaction queue which operates the data storage device within the power/current target.

Western Digital

WESTERN DIGITAL CORPORATION

(Exact Name of Registrant as Specified in Its Charter)

Item 1. ***Business***

General

We are a leading developer, manufacturer and provider of data storage solutions that enable consumers, businesses, governments and other organizations to create, manage, experience and preserve digital content. Our product portfolio includes hard disk drives ("HDDs"), solid-state drives ("SSDs"), direct attached storage solutions, personal cloud network attached storage solutions, and public and private cloud data center storage solutions. HDDs are our principal products and are today's primary storage medium for the vast majority of digital content, with the use of solid-state storage products growing rapidly. Our products are marketed under the HGST, WD and G-Technology brand names.

Data Storage Solutions

We offer a broad line of data storage solutions to meet the evolving storage needs of our end users. HGST's HDD offerings include: high performance 10,000/15,000 revolutions per minute ("RPM") drives targeting server and storage system OEMs, enterprise capacity drives for bulk storage applications for both hyperscale cloud customers and OEMs, the industry's only helium sealed drives featuring capacities of up to 10 terabytes ("TB") to deliver unmatched total cost of ownership, mobile drives for the notebook, PC and gaming markets, a G-Technology line of branded products for professional content producers, enterprise storage software and a fully integrated active archive system. HGST also delivers a line of SSDs for servers and storage systems applications that includes 2.5" serial attached SCSI (Small Computer System Interface) ("SAS") drives as well as peripheral component interconnect express ("PCIe") NVMe SSDs and embedded flash solutions. Our WD subsidiary designs, manufacturers and provides hard drives for a wide range of digital storage uses, from PCs and data centers to video recording systems, home network storage devices, and video surveillance. WD also packages these hard drives into consumer appliances, which offer portable, desktop and personal cloud storage for accessibility from anywhere and sharing functionality.

Consumer Electronics Solutions. CE solutions are used in DVRs, gaming consoles, security surveillance, systems, set top boxes, camcorders, multi-function printers and entertainment and automobile navigation systems. Our CE solutions include HDDs designed and optimized for video streaming and continuous digital video recording. These HDDs deliver quiet operation, low operating temperature, low power consumption, high reliability and optimized streaming capabilities. Our CE HDD unit shipments were 37 million, 37 million and 28 million for 2015, 2014 and 2013, respectively.

This figure provides an example of climate patent and illustrates how we measure the relatedness between a climate patent and the product portfolio of the firm holding the patent. To extract patent content, we follow the approach of Kogan et al. (2021), using text from the title, abstract, and detailed description sections. Product descriptions are drawn from Item 1 (Business Description) of 10-K filings, following Hoberg and Phillips (2016). We compute the pairwise textual similarity between the climate patent and product description using the Stanford GloVe (Global Vectors for Word Representation) model. Our analysis focuses on noun phrases and applies term frequency–inverse document frequency (TF-IDF) weighting. For methodological details, see Kogan et al. (2021). The figure provides an example based on the climate patent titled "Enhanced Queue Management for Power Control of Data Storage Device," identified as a climate-related innovation via its Y02D classification. The patent is assigned to Western Digital Corporation, and we match it to the firm's 10-K Item 1 filing from the same year as the patent application.

Figure 2. The Illustration of Identification Strategy for Extensive Margin

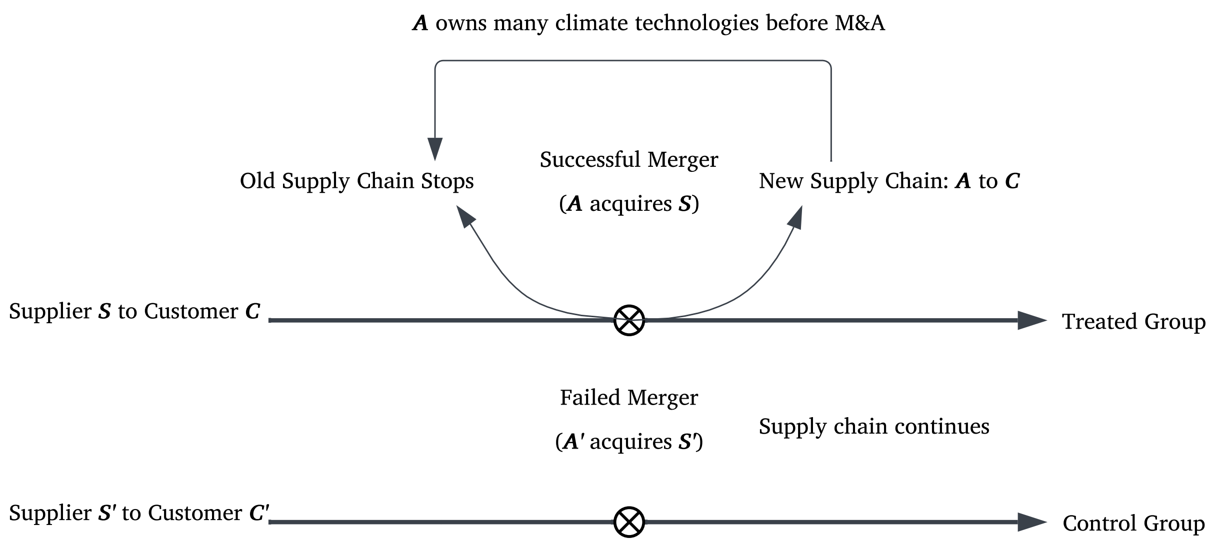
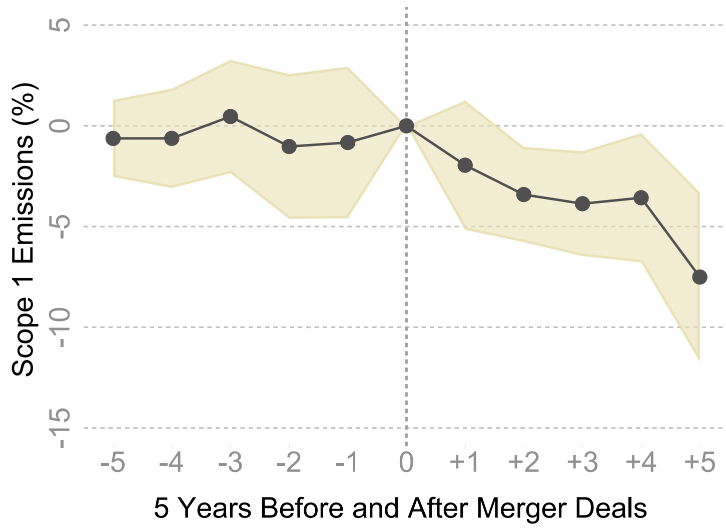


Figure 2 illustrates our identification strategy for the extensive margin, i.e. the effect of suppliers' climate innovation on emission reductions for newly acquired customer firms. We exploit successful and failed mergers to introduce exogenous variation in supply chain switching. In the above example, supplier S serves customer C, and supplier S' serves customer C'. Both S and S' are targets in merger attempts; S is successfully acquired by firm A, while the deal involving S' fails. Following the acquisition, customer C may switch from sourcing inputs from S to sourcing from the acquirer, A. We further identify that A holds a substantial fraction of climate-related patents—more than 5% of its total—prior to the merger. We interpret the formation of this new supply chain link, with a climate-innovative supplier, as plausibly exogenous.

Figure 3. Diff-in-Diff Analysis of Customer Emission After Successful vs. Failed Supplier Mergers

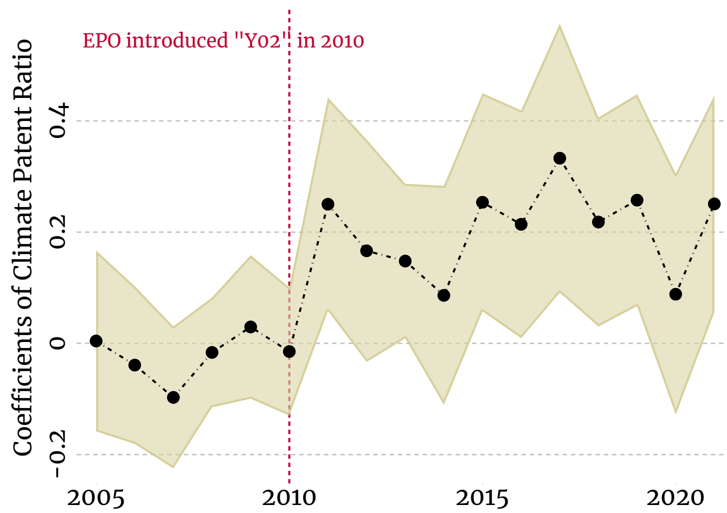


This figure presents the results of a Difference-in-Differences analysis examining the extensive margin of emission reduction by climate innovation, using successful versus failed mergers as exogenous variation in supply chain disruptions. The identification strategy underlying this analysis is illustrated in Figure 2, and the construction of treatment and control groups is detailed in Table 8, Panel A. The figure plots the estimated coefficients $\beta_{1,k}$ for $k = -5$ to $+5$ from the following event-study specification:

$$Ln(\text{Scope 1 Emissions})_{i,t} = \sum_{k=-5}^{+5} \beta_{1,k} \left(\mathbb{I}[\text{Surround Year k}]_{i,t} \times \mathbb{I}[\text{Successful Merger}]_{i,t}\right) + \sum_{k=-5}^{+5} \beta_{2,k} \mathbb{I}[\text{Surround Year k}]_{i,t} + \beta_3 X_{i,t} + \chi_i + \nu_t + \varepsilon_{i,t} \quad (6)$$

where the dependent variable is the natural logarithm of firm i's Scope 1 emissions in year t. The indicator $\mathbb{I}[\text{Surround Year } k]_{i,t}$ equals one if year t is k years relative to the merger year (where $k \in [-5, +5]$). The variable $\mathbb{I}[\text{Successful Merger}]_t$ is a dummy equal to one for observations associated with successful mergers. Control variables ($X_{i,t}$), all measured at $t-1$, include firm size, Tobin's q, cash holdings, book leverage, return on assets (ROA), capital expenditures, and sales growth. The model includes firm fixed effects (χ_i) and year fixed effects (ν_t). Standard errors are clustered at the industry and year levels. The figure reports 90% confidence intervals around the estimated coefficients.

Figure 4. Supplier's Climate Patent Ratio and Number of New Customer Firms

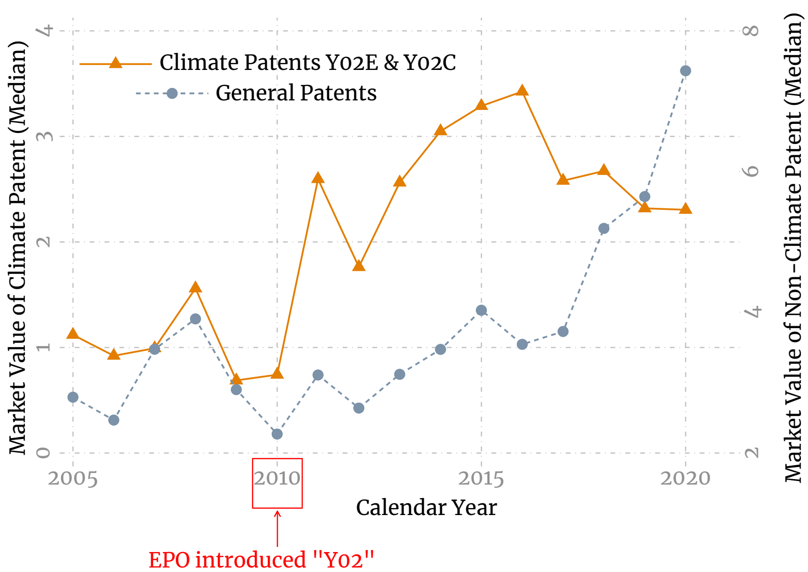


This figure examines the relationship between the climate patent ratio and the number of new customers attracted by each supplier firm. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t\Big) + \\ \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t}\,, \quad (7)$$

where $Num\_New\_Customer\_Firms_{i,t}$ denotes the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. The dependent variable is transformed using the natural logarithm of $(1 + x)$. The variable $Clim\_Patent\_Ratio_{i,\mathbf{t\text{-}1}}$ represents the ratio of climate-related patents (Y02) newly granted to the firm to all patents granted to the same firm in year $t - 1$. The regression model contains control variables for firm-specific factors, such as firm size, Tobin's q, cash, book leverage, ROA, capital expenditure, sales growth, and the count of existing customers. These variables are measured in year $t - 1$. Additionally, industry (NAICS 4-digit) $\times$ year fixed effects are included. Standard errors are clustered at the firm level, and the confidence intervals depicted in the figure denote a 90% confidence level.

Figure 5. Market Response to Climate Patent Granting



This figure illustrates the annual median market response to the granting of climate patents and general patents. The analysis includes all US patents granted to CRSP-Compustat firms, as detailed in Kogan et al. (2017). The market value of patents, assessed as per Kogan et al. (2017), serves as the measure for evaluating the market reaction. The orange line represents the median annual market value (in millions) for climate-related patents falling within the Y02E and Y02C categories. Notably, these categories were identified as climate change mitigation patents (CCMT) by the European Patent Office (EPO) back in 2010. Conversely, the dark blue line depicts the median annual market value (in millions) for all general patents, not specifically related to climate aspects.

Table 1. Summary Statistics: Supplier-Customer Relationships

This table presents summary statistics based on our supply chain data at the level of supplier-customer relationships. To construct this dataset, we combine the FactSet Revere and Compustat customer segment datasets, following the methodology outlined in Schiller (2018). In Panel A, we provide summary statistics for the full sample, covering the period from 2003 to 2021. The dataset comprises a total of 73,477 unique supplier-customer relationships. Each observation represents a unique supplier-customer pair with start date and end date. Following Barrot and Sauvagnat (2016), we consider firm A to be a supplier to firm C in all years from the first to the last year that A reports C as one of its customers. Panel B presents similar summary statistics, but only for supplier-customer relationships with non-missing sales information. This allows us to focus on relationships where sales data is available and provides a more detailed understanding of the characteristics of these relationships. In Panel C, we present the industry distribution of both suppliers and customers. Industries are classified using the NAICS (North American Industry Classification System) at the 2-digit level. We highlight industry frequencies that exceed 2% to emphasize the most prevalent industries in the dataset.

Number of Supply Chain Relationships	Number	Percentage
Panel A: Full Sample (2003 – 2021)		
Compustat Supplier and Compustat Customer	73,447	100%
+ Customer Firm with ESG Score (Refinitiv + S&P Global + Sustainalytics)	48,563	66%
By Duration Years		
1 year or less than 1 year	14,261	29%
2 years	6,971	14%
3 years	3,683	8%
4 years	2,387	5%
5 years and more	6,499	13%
Ongoing	14,762	30%
Panel B: Subsample (2003 – 2021) with Available Sales Data		
Compustat Supplier and Compustat Customer	9,118	100%
+ Customer Firm with Emission Data from Trucost	3,574	39%
By Duration Years		
1 year or less than 1 year	1,620	45%
2 years	512	14%
3 years	353	10%
4 years	271	8%
5 years and more (or ongoing)	818	23%

Table 1 – continued from previous page

Panel C: Industry Distribution of Supply Chain Relationships

Supplier's Industry \ Customer's Industry	Agriculture (11)	Mining (21)	Utilities (22)	Construct--ions (23)	Manufac--turing (31)	Manufac--turing (32)	Manufac--turing (33)	Wholesale Trade (42)	Retail Trade (44)	Retail Trade (45)	Transport--ation (48)	Transport--ation (49)
Agriculture (11)	0.00%	0.00%	0.00%	0.01%	0.01%	0.01%	0.00%	0.01%	0.01%	0.01%	0.00%	0.00%
Mining (21)	0.00%	1.27%	0.44%	0.01%	0.00%	0.48%	0.06%	0.12%	0.01%	0.02%	0.30%	0.02%
Utilities (22)	0.00%	0.20%	1.01%	0.01%	0.02%	0.17%	0.16%	0.04%	0.03%	0.03%	0.14%	0.01%
Constructions (23)	0.00%	0.10%	0.30%	0.05%	0.01%	0.20%	0.08%	0.02%	0.03%	0.01%	0.08%	0.00%
Manufacturing (31)	0.00%	0.02%	0.00%	0.00%	0.30%	0.14%	0.12%	0.22%	0.68%	0.77%	0.02%	0.00%
Manufacturing (32)	0.00%	0.14%	0.13%	0.09%	0.39%	4.01%	1.12%	1.16%	0.76%	0.56%	0.17%	0.02%
Manufacturing (33)	0.01%	0.57%	0.63%	0.21%	0.51%	1.93%	12.47%	2.34%	1.19%	1.43%	0.51%	0.14%
Wholesale Trade (42)	0.00%	0.15%	0.09%	0.01%	0.10%	0.40%	0.60%	0.16%	0.20%	0.17%	0.11%	0.01%
Retail Trade (44)	0.00%	0.00%	0.03%	0.02%	0.02%	0.04%	0.05%	0.01%	0.08%	0.11%	0.02%	0.01%
Retail Trade (45)	0.00%	0.06%	0.02%	0.00%	0.08%	0.09%	0.19%	0.03%	0.11%	0.16%	0.04%	0.01%
Transportation (48)	0.00%	0.58%	0.42%	0.00%	0.12%	0.76%	0.20%	0.07%	0.06%	0.11%	0.48%	0.04%
Transportation (49)	0.00%	0.00%	0.00%	0.00%	0.01%	0.04%	0.07%	0.04%	0.04%	0.08%	0.01%	0.01%
Information (51)	0.01%	0.16%	0.34%	0.07%	0.79%	1.55%	4.15%	0.79%	1.06%	1.14%	0.56%	0.13%
Finance (52)	0.00%	0.18%	0.09%	0.01%	0.07%	0.22%	0.29%	0.05%	0.34%	0.24%	0.11%	0.02%
Real Estate (53)	0.00%	0.14%	0.06%	0.01%	0.14%	0.35%	0.64%	0.09%	0.93%	0.58%	0.11%	0.06%
Technical Services (54)	0.01%	0.12%	0.35%	0.04%	0.25%	0.94%	1.24%	0.23%	0.32%	0.25%	0.15%	0.04%
Administrative Service (56)	0.00%	0.04%	0.09%	0.02%	0.02%	0.17%	0.20%	0.04%	0.06%	0.05%	0.05%	0.01%
Educational Services (61)	0.00%	0.00%	0.03%	0.00%	0.01%	0.05%	0.08%	0.01%	0.01%	0.00%	0.01%	0.01%
Health Care (62)	0.00%	0.00%	0.01%	0.00%	0.01%	0.10%	0.06%	0.01%	0.04%	0.01%	0.01%	0.00%
Entertainment (71)	0.00%	0.00%	0.01%	0.00%	0.05%	0.02%	0.04%	0.00%	0.02%	0.00%	0.01%	0.00%
Accommodation and Food (72)	0.00%	0.00%	0.00%	0.00%	0.09%	0.01%	0.03%	0.02%	0.04%	0.05%	0.02%	0.00%
Other Services (81)	0.00%	0.00%	0.01%	0.00%	0.01%	0.01%	0.01%	0.00%	0.01%	0.01%	0.01%	0.00%
Public Administration (92)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Continued	Information (51)	Finance (52)	Real Es-tate (53)	Technical Services (54)	Adminis--trative Service (56)	Educat--ional Services (61)	Health Care (62)	Enterta--inment (71)	Accomm--odation and Food (72)	Other Services (81)	Public Admini--stration (92)	Unknown (99)
Agriculture (11)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.02%	0.00%	0.00%	0.00%
Mining (21)	0.01%	0.08%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Utilities (22)	0.05%	0.05%	0.02%	0.00%	0.01%	0.00%	0.00%	0.00%	0.03%	0.00%	0.00%	0.01%
Constructions (23)	0.09%	0.03%	0.01%	0.02%	0.00%	0.00%	0.00%	0.00%	0.01%	0.00%	0.00%	0.01%
Manufacturing (31)	0.04%	0.01%	0.03%	0.01%	0.00%	0.00%	0.00%	0.02%	0.29%	0.00%	0.00%	0.01%
Manufacturing (32)	0.15%	0.22%	0.04%	0.09%	0.01%	0.00%	0.12%	0.01%	0.11%	0.01%	0.00%	0.08%
Manufacturing (33)	2.82%	0.55%	0.36%	0.97%	0.10%	0.05%	0.20%	0.09%	0.43%	0.02%	0.00%	0.44%
Wholesale Trade (42)	0.16%	0.08%	0.03%	0.06%	0.01%	0.01%	0.03%	0.01%	0.09%	0.00%	0.00%	0.03%
Retail Trade (44)	0.06%	0.09%	0.01%	0.01%	0.01%	0.00%	0.01%	0.01%	0.01%	0.00%	0.00%	0.00%
Retail Trade (45)	0.49%	0.08%	0.03%	0.08%	0.03%	0.01%	0.01%	0.00%	0.04%	0.01%	0.00%	0.01%
Transportation (48)	0.04%	0.05%	0.04%	0.01%	0.01%	0.00%	0.00%	0.01%	0.04%	0.01%	0.00%	0.02%
Transportation (49)	0.03%	0.00%	0.00%	0.01%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Information (51)	6.84%	3.13%	0.50%	1.44%	0.37%	0.09%	0.22%	0.16%	0.79%	0.04%	0.00%	0.19%
Finance (52)	0.67%	2.71%	0.11%	0.11%	0.06%	0.01%	0.05%	0.02%	0.09%	0.01%	0.00%	0.02%
Real Estate (53)	0.68%	0.44%	0.18%	0.16%	0.04%	0.02%	0.09%	0.04%	0.19%	0.00%	0.00%	0.03%
Technical Services (54)	1.15%	0.76%	0.11%	0.34%	0.08%	0.02%	0.07%	0.01%	0.18%	0.00%	0.00%	0.09%
Administrative Service (56)	0.19%	0.20%	0.05%	0.08%	0.05%	0.00%	0.03%	0.00%	0.04%	0.00%	0.00%	0.02%
Educational Services (61)	0.03%	0.05%	0.00%	0.01%	0.01%	0.01%	0.00%	0.00%	0.01%	0.00%	0.00%	0.01%
Health Care (62)	0.05%	0.18%	0.02%	0.01%	0.00%	0.00%	0.09%	0.00%	0.01%	0.00%	0.00%	0.01%
Entertainment (71)	0.08%	0.02%	0.01%	0.00%	0.01%	0.00%	0.00%	0.03%	0.04%	0.00%	0.00%	0.00%
Accommodation and Food (72)	0.04%	0.03%	0.10%	0.00%	0.00%	0.00%	0.00%	0.02%	0.09%	0.00%	0.00%	0.00%
Other Services (81)	0.02%	0.02%	0.03%	0.00%	0.00%	0.00%	0.00%	0.01%	0.02%	0.00%	0.00%	0.00%
Public Administration (92)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table 2. Summary Statistics: Firm-Level Observations

This table presents summary statistics at the firm level. Panel A provides statistics for the customer sample, which consists of firms that have at least one supplier firm selling products or services to them. Only supplier-customer relationships with available sales information are included in the analysis. Firms in the financial, retail, and wholesale sectors, as well as those without CO2 emission information from Trucost, are excluded from the sample. Panel B presents summary statistics for the Compustat sample, which includes firms that have established new supplier-customer relationships with at least one customer between 2005 and 2021. Firms in the financial, retail, and wholesale industries are excluded from this sample. Panel C displays the pairwise correlations between environmental scores obtained from three ESG (Environmental, Social, and Governance) databases. Finally, Panel D reports the pairwise correlations between greenhouse gas (GHG) emissions (both total and intensity) and our composite ESG score. Log denotes the $ln(1+x)$ transformation.

Panel A: Customer Sample

Variable	Mean	p50	p75	p90	SD	N
Supplier's Climate Patent Ratio	0.016	0.000	0.000	0.038	0.059	2,831
Supplier's Number of General Patents	28.906	0.000	4.095	25.872	165.328	2,831
Customer's Climate Patent Ratio	0.054	0.000	0.046	0.167	0.127	2,831
Number of Suppliers	4.720	2.000	5.000	12.000	6.240	2,831
Firm Size	10.010	10.149	11.027	11.841	1.480	2,830
Ln(Firm Age)	3.916	4.094	4.635	4.898	0.898	2,769
PPE	8.306	8.496	9.585	10.085	1.557	2,413
Sales Growth	0.095	0.065	0.164	0.318	0.251	2,785
Ln(Scope 1 Emissions)	13.019	12.867	14.740	17.100	2.673	2,831
Scope 1 Emission Intensity	3.923	3.493	5.526	6.863	2.097	2,738

Panel B: Compustat Sample (Suppliers)

Variable	Mean	p50	p75	p90	SD	N
Number of New Customer Firms (log)	0.340	0.000	0.693	1.099	0.584	41,777
Number of New Customer Firms (High E-score) (log)	0.197	0.000	0.000	0.693	0.438	41,777
Number of New Customer Firms (Low E-score) (log)	0.201	0.000	0.000	0.693	0.421	41,777
Number of Existing Customer Firms (log)	1.269	1.099	2.079	2.773	1.038	41,777
Climate Patent Ratio	0.021	0.000	0.000	0.047	0.106	41,777
Number of General Patents (log)	0.841	0.000	1.099	3.045	1.478	41,777
Firm Size	6.661	6.678	8.180	9.499	2.170	41,766
Tobin's Q	2.109	1.564	2.422	3.919	1.617	39,039
Cash	0.219	0.127	0.322	0.597	0.236	41,209
Book Leverage	0.346	0.310	0.537	0.746	0.320	40,913
ROA	0.055	0.104	0.165	0.235	0.229	37,988
CAPX	0.047	0.029	0.058	0.107	0.058	39,084
Sales Growth	0.126	0.068	0.199	0.427	0.434	38,543

Panel C: Pairwise Correlations among Environmental Scores of Different Providers

Pairwise Correlation	Environmental Score Provider		
Environmental Score Providers	LSEG	S&P Global	Sustainalytics
LSEG (formerly Refinitiv)	1.000		
S&P Global	0.660	1.000	
Sustainalytics	0.665	0.711	1.000

Panel D: Pairwise Correlation between ESG Scores and Emissions

Pairwise Correlation

	Environmental Score	ESC Management	GHG Emission Total	GHG Emission Intensity
Environmental Score	1.000			
ESC Management Dummy	0.639	1.000		
GHG Emission (Total)	0.185	0.113	1.000	
GHG Emission (Intensity)	0.122	0.041	0.589	1.000

Table 3. Supplier's Climate Patents and Customer's CO2 Emission Changes

This table examines the relationship between changes in a customer firm's CO2 emissions and the climate patent ratio of its suppliers. The sample used in the regressions follows Table 2, Panel A. Each observation in the customer sample represents a firm-year observation with at least one supplier firm that sold products or services to the given firm in that specific year. We only include supplier-customer relationships with non-missing sales information. Customer firms in the financial, retail, and wholesale sectors are excluded from the sample. Additionally, firms without CO2 emission information from Trucost are also excluded. The dependent variable in Panel A (Panel B) is the change in Scope 1 (Scope 2) CO2 emissions from year t to $t + k$. Total emissions is represented by the natural logarithm of CO2 emissions in tons, and emission intensity is calculated as the natural logarithm of total emissions divided by output. The main independent variable, Supplier's Climate Patent Ratio [t], is the weighted climate patent ratio of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate patents newly invented divided by the total number of patents invented in year t. Firm controls include firm size, Tobin's q, cash, book leverage, return on assets (ROA), capital expenditures, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) × year fixed effects. To enhance readability, coefficients are multiplied by 100. Standard errors are clustered at the firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Scope 1 CO2 Emissions

Change of Scope 1 CO2 Emissions	(1) t+1 - t	(2)	(3) t+2 - t	(4)	(5) t+3 - t	(6)	(7) t+4 - t	(8)	(9) t+5 - t	(10)
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-2.358**	-2.413**	-4.401**	-4.242**	-6.383**	-6.531***	-8.200**	-8.245***	-10.840***	-12.380***
	(1.084)	(1.150)	(2.014)	(1.837)	(2.689)	(2.440)	(3.195)	(3.092)	(3.727)	(3.572)
Supplier's Number of General Patent [t]	0.002	-0.330	0.481	0.568	-0.042	0.420	-1.247	-1.050	-1.138	-1.215
	(1.014)	(1.028)	(2.104)	(1.942)	(3.028)	(2.717)	(3.972)	(3.616)	(4.812)	(4.659)
Customer's Climate Patent Ratio [t]	1.412	1.179	2.310	2.402*	1.050	1.355	0.383	1.052	0.931	-0.720
	(1.029)	(0.805)	(1.557)	(1.388)	(2.462)	(2.451)	(2.618)	(2.208)	(2.956)	(2.241)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.099	0.073	0.131	0.102	0.151	0.119	0.155	0.165	0.185	0.218

Panel B: Scope 2 CO2 Emissions

Change of Scope 2 CO2 Emissions	(1) t+1 - t	(2)	(3) t+2 - t	(4)	(5) t+3 - t	(6)	(7) t+4 - t	(8)	(9) t+5 - t	(10)
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-1.208	-0.938	-6.178***	-5.345***	-6.542**	-5.695**	-8.074**	-7.184**	-5.852*	-6.215**
	(1.426)	(1.214)	(2.371)	(1.909)	(2.783)	(2.201)	(3.511)	(3.032)	(3.524)	(2.533)
Supplier's Number of General Patent [t]	0.231	-0.345	1.615	1.058	1.458	1.308	1.149	0.557	-1.590	-1.883
	(1.184)	(0.994)	(1.931)	(1.548)	(2.741)	(2.052)	(3.751)	(2.763)	(4.762)	(3.692)
Customer's Climate Patent Ratio [t]	-0.419	-1.122	-1.080	-1.274	-1.104	-1.329	-1.049	-0.021	3.665	1.501
	(1.388)	(1.203)	(2.781)	(1.809)	(2.955)	(2.381)	(4.045)	(3.126)	(5.656)	(4.327)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.098	0.071	0.132	0.104	0.153	0.121	0.157	0.167	0.182	0.210

Table 4. Supplier's Climate Patents and Customer's CO2 Emission Changes (Alternative Setups)

This table presents regression results of Table 3 using alternative setups. In Panel A, we include supplier-customer relationships with both non-missing and missing supplier-to-customer sales information when we construct the customer sample and calculate the weighted climate patent ratio of suppliers. We use the supplier's annual total sales from Compustat as weights. In Panel B, we introduce an interaction term between the supplier's climate patent ratio and the initial Scope 1 emissions of customers measured at year t. In Panel C, we differentiate between product and process patents and define two separate measures: the climate patent ratio (process) and the climate patent ratio (product). We classify climate patents into climate process patents and climate product patents, following the method for general patents developed by Bena et al. (2022) and Ma (2022). Standard errors are clustered at the customer-firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively. To enhance readability, coefficients are multiplied by 100.

Panel A: Full Sample Incl. Missing Supplier-Customer Sales (Alternative Weighting Method)

Change in Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-2.276***	-1.783***	-2.737**	-2.079*	-3.598**	-1.624	-2.803	-0.831	-4.900**	-2.620
	(0.740)	(0.643)	(1.182)	(1.106)	(1.576)	(1.419)	(2.043)	(1.698)	(2.348)	(2.099)
Supplier's General Patent Number [t]	1.714**	1.011	2.956**	2.060	4.172**	2.704	6.832***	4.191*	8.974***	5.412*
	(0.783)	(0.658)	(1.399)	(1.277)	(1.902)	(1.756)	(2.464)	(2.238)	(3.279)	(3.039)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	5733	5605	5693	5552	4852	4717	3999	3875	3228	3117
Adjusted R^2	0.101	0.113	0.119	0.124	0.150	0.150	0.176	0.185	0.203	0.224

Panel B: Interaction with Prior Customer Emissions

Change in Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	0.500	0.532	0.153	0.745	-2.161	-1.094	-1.862	-0.714	3.091	-3.589
	(3.671)	(1.686)	(7.221)	(2.389)	(11.372)	(3.728)	(13.431)	(4.285)	(14.812)	(5.384)
Supplier's Climate Patent Ratio [t] × Scope 1 Emissions (Total) [t]	-0.192		-0.306		-0.292		-0.446		-0.956	
	(0.262)		(0.508)		(0.803)		(0.968)		(1.032)	
Supplier's Climate Patent Ratio [t] × Scope 1 Emissions (Intensity) [t]		-0.574**		-0.962***		-1.071*		-1.466**		-1.676**
		(0.269)		(0.361)		(0.585)		(0.674)		(0.796)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.110	0.079	0.165	0.121	0.202	0.142	0.239	0.192	0.323	0.254

Panel C: Product Patents vs. Process Patents

Change in Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t] (Process Patent)	-2.066	-0.973	-4.072	-3.985	-2.330	-3.551	-4.504	-6.954**	-2.162	-2.613
	(2.319)	(2.294)	(2.691)	(2.632)	(2.756)	(3.215)	(3.481)	(3.366)	(4.070)	(3.881)
Supplier's Climate Patent Ratio [t] (Product Patent)	0.011	-1.314	-1.776	-2.511	-6.811**	-6.448	-8.621***	-6.756*	-10.957***	-13.722***
	(1.537)	(1.339)	(2.436)	(2.547)	(3.078)	(3.976)	(2.926)	(3.890)	(3.013)	(2.700)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.110	0.079	0.165	0.121	0.202	0.142	0.239	0.192	0.323	0.254

Panel D: By Y02 Categories										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Y02B: Green Building										
Supplier's Climate Patent Ratio [t]	-1.550	-3.124*	-5.097***	-6.851***	-7.292**	-8.792***	-9.764**	-11.206**	-8.761*	-13.429**
	(1.302)	(1.829)	(1.764)	(2.055)	(2.903)	(3.277)	(4.535)	(4.862)	(4.457)	(5.198)
Y02C: CO2 Capture and Storage										
Supplier's Climate Patent Ratio [t]	-2.377	-5.866**	-5.313	-10.254***	-0.043	-5.981	1.383	-5.717	-4.368	-17.491**
	(3.236)	(2.835)	(5.249)	(3.834)	(5.579)	(7.000)	(6.372)	(8.493)	(7.871)	(7.583)
Y02D: ICT										
Supplier's Climate Patent Ratio [t]	0.452	0.088	-3.037*	-3.063*	-7.341**	-7.430**	-6.635	-5.386	-8.873*	-8.948*
	(1.193)	(1.239)	(1.821)	(1.781)	(3.031)	(3.074)	(4.065)	(3.966)	(5.263)	(4.833)
Y02E: Energy										
Supplier's Climate Patent Ratio [t]	-1.202	-1.625	-2.791	-2.886	-4.530*	-3.835	-5.804**	-4.729*	-6.506**	-7.626**
	(1.542)	(1.613)	(2.159)	(2.245)	(2.649)	(3.136)	(2.849)	(3.146)	(3.201)	(3.866)
Y02P: Goods Production										
Supplier's Climate Patent Ratio [t]	-0.190	-0.136	2.446	1.985	-1.123	-2.636	-5.866	-6.747	-8.573	-9.505
	(1.489)	(1.482)	(2.291)	(2.175)	(4.273)	(3.662)	(6.546)	(5.840)	(8.524)	(8.256)
Y02T: Transportation										
Supplier's Climate Patent Ratio [t]	-1.165	-0.937	-3.871**	-3.136**	-3.776	-3.794**	-3.853	-5.342**	-6.877*	-7.961**
	(1.011)	(0.707)	(1.859)	(1.502)	(2.691)	(1.810)	(3.639)	(2.480)	(3.906)	(3.374)

Table 5. Supplier's Climate Innovation and Customer's CO2 Emissions (Supplier-Customer Pair Sample)

This table presents the results of OLS regressions based on a supplier-customer pair sample. Each observation represents a supplier $\times$ customer $\times$ year, indicating that the supplier sells goods or services to the customer in that specific year. It is not necessary for the supplier-to-customer sale to be non-missing. The dependent variable is the customer's future Scope 1 (Scope 2 in Panel B) CO2 emissions in year $t+k$, where $k = 1, 2$, and 3. The variable "*Supplier's Climate Patent Ratio [t]*" represents the ratio of newly invented climate patents in year t by the supplier in the given supplier-customer pair. The variable "Supplier's General Patent Number [t]" denotes the total number of newly invented general patents in year t by the supplier. Fixed effects for supplier $\times$ customer pairs are consistently included. Standard errors are clustered at the customer-firm level. Statistical significance is denoted by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. To enhance readability, all coefficients are multiplied by 100.

Panel A: Supplier-Customer Pair Sample (Scope 1 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 1 Emission Total			Scope 1 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Supplier's Climate Patent Ratio [t]	-4.699***	-4.280***	-4.474***	-4.433***	-4.341***	-4.132***
	(1.254)	(1.500)	(1.525)	(1.200)	(1.436)	(1.393)
Supplier's General Patent Number [t]	1.932	2.362	0.471	2.556	2.571	0.065
	(1.878)	(2.234)	(2.454)	(1.822)	(2.112)	(2.192)
Customer Firm Controls	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	47674	35308	26430	47205	34971	26169
Adj R^2	0.971	0.970	0.969	0.964	0.965	0.968

Panel B: Supplier-Customer Pair Sample (Scope 2 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 2 Emission Total			Scope 2 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Supplier's Climate Patent Ratio [t]	-2.558**	-2.223	-1.622	-2.290*	-2.274	-1.334
	(1.239)	(1.644)	(1.844)	(1.195)	(1.564)	(1.747)
Supplier's General Patent Number [t]	-1.243	-0.657	-1.365	-0.894	-0.593	-2.049
	(1.667)	(2.089)	(2.464)	(1.578)	(1.961)	(2.275)
Customer Firm Controls	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	47634	35279	26403	47165	34942	26142
Adj R^2	0.928	0.916	0.907	0.813	0.794	0.786

Table 6. Supplier's Climate Innovation and Customer's Emissions (State R&D Tax Credits)

This table repeats the analyses in Table 5 using US state-level R&D tax credits as an exogenous shock to the invention of new climate patents by suppliers. In Panel A, we present the first-stage regressions using the supplier-customer pair sample. The state-level R&D tax credit data are from the Panel Database on Incentives and Taxes (PDIT), which calculates tax credits as percentage of average value-added of companies in a given industry within a given state. We use the average tax credits of all industries in a given state as our independent variable in Panel A. In Panels B and C, we present the second-stage regression, where the number of climate patents (by suppliers) is instrumented by R&D tax credits. Fixed effects for supplier × customer pairs are consistently included. Standard errors are clustered at the customer-firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. For ease of interpretation, all coefficients are multiplied by 100.

Panel A: The First Stage Regression						
	(1)	(2)	(3)	(4)	(5)	(6)
First Stage	Number of Climate Patents by Suppliers			Number of General Patents by Suppliers		
State R&D Tax Credits [*t*-1]	2.444***			0.638		
	(0.465)			(0.562)		
State R&D Tax Credits [*t*-2]		2.018***			1.204**	
		(0.392)			(0.485)	
State R&D Tax Credits [*t*-3]			2.373***			1.462***
			(0.393)			(0.482)
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Calendar Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	47673	47673	47673	47673	47673	47673
adj. R^2	0.936	0.936	0.936	0.955	0.955	0.955

Panel B: Supplier-Customer Pair Sample (Scope 1 Emissions)						
2SLS Regression	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 1 Emission Total			Scope 1 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Number of Climate Patents by Suppliers [t]	-0.139	-0.647*	-1.146**	-0.171	-0.665**	-1.049**
(*Instrumented by State R&D Credits [t-3]*)	(0.181)	(0.358)	(0.525)	(0.168)	(0.330)	(0.490)
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Calendar Year F.E.	Y	Y	Y	Y	Y	Y
Weak Instrument F-Test	36.49	28.03	19.07	36.97	29.90	19.74
Num. Obs.	47673	35260	26381	47147	34851	26060

Panel C: Supplier-Customer Pair Sample (Scope 2 Emissions)						
2SLS Regression	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 2 Emission Total			Scope 2 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Number of Climate Patents by Suppliers [t]	-0.021	-0.178	-0.247	-0.294	-0.478	-0.340
(*Instrumented by State R&D Credits [t-3]*)	(0.222)	(0.388)	(0.666)	(0.220)	(0.375)	(0.654)
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Calendar Year F.E.	Y	Y	Y	Y	Y	Y
Weak Instrument F-Test	36.49	28.03	19.07	36.97	29.90	19.74
Num. Obs.	47673	35260	26381	47147	34851	26060

Table 7. Customer's CO2 Emission Reductions: New and Old Suppliers

This table examines the relationship between changes in a customer firm's CO2 emissions and the presence of new and old suppliers. The regression sample includes firms both with and without supply-chain relationships in year t. The dependent variables are consistent with those in Table 3. The main independent variable, "I[New Supplier with Climate Patents]," is a dummy variable equal to 1 if the firm acquires a new supplier with a climate patent ratio greater than 0.2 in year t. The climate patent ratio is calculated using the supplier's patent information from years $t-2$, $t-1$, and t. The variable "I[Old Supplier with Climate Patents]" is a dummy variable equal to 1 if the firm has long-standing suppliers (relationships starting 5 years ago) with a climate patent ratio (in years $t-2$, $t-1$, and t) greater than 0.2. Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) × year fixed effects. Standard errors are clustered at the industry level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively. To enhance readability, coefficients are multiplied by 100.

Panel A: Scope 1 CO2 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
I[New Supplier with Climate Patents]	-1.986	-0.922	-5.022*	-4.474*	-8.548***	-6.593**	-9.765**	-7.182*	-11.134**	-10.476**
	(1.586)	(1.417)	(2.732)	(2.488)	(3.134)	(3.055)	(4.249)	(3.907)	(4.614)	(4.261)
I[Old Supplier with Climate Patents]	-1.743	-1.830	-3.370	-3.396*	-5.597**	-6.573***	-1.770	-4.763	-2.610	-5.774
	(1.615)	(1.413)	(2.353)	(2.040)	(2.816)	(2.521)	(3.884)	(3.282)	(4.958)	(4.311)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	15849	15526	13541	13229	11476	11188	9573	9316	7812	7593
Adj. R^2	0.015	0.030	0.046	0.036	0.059	0.041	0.071	0.058	0.092	0.081
Panel B: Scope 2 CO2 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 2 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
I[New Supplier with Climate Patents]	-3.226*	-2.273	-6.064**	-5.389**	-7.959**	-5.048	-10.968**	-8.039**	-16.916***	-16.025***
	(1.693)	(1.444)	(2.736)	(2.425)	(3.631)	(3.232)	(4.302)	(3.824)	(5.887)	(5.678)
I[Old Supplier with Climate Patents]	-1.973	-1.798	-5.563**	-5.510**	-6.330**	-6.332**	-6.301	-7.591	-5.490	-4.363
	(1.630)	(1.404)	(2.639)	(2.346)	(3.205)	(2.755)	(5.073)	(4.656)	(7.326)	(6.689)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	15856	15533	13547	13235	11479	11191	9577	9320	7816	7597
Adj. R^2	0.065	0.060	0.108	0.085	0.136	0.116	0.173	0.149	0.216	0.192

Table 8. Supplier Mergers and Diff-in-Diff Analysis of the Extensive Margin

This table presents estimation results for our difference-in-differences analysis of supply chain reconfiguration due to suppliers targeted in merger bids, along with summary statistics for the construction of the treatment and control groups. Panel A reports summary statistics. The procedures for defining the treated and control groups follow the approach described in the text and illustrated in Figure 2. The term "*(of which)*" indicates the sequential application of additional sample filters relative to the preceding row. *Old Supply Chain Terminated due to Supplier Merger* refers to supplier–customer relationships in which the supplier is successfully acquired and the relationship is terminated either in the merger completion year or the preceding year. *Supply Chain Switches to Old Supplier's Acquirer as New Supplier* captures the subset of all cases in which the customer subsequently switches to its old supplier's acquirer as its new supplier, with the new relationship beginning in the merger year or the following 2 years. The final treatment and control groups include 33 and 169 supply chain relationships, respectively. Panel B reports the estimated coefficients for the difference-in-differences regressions. The dependent variable is the carbon emissions of customer firms. The regression sample includes all firm-year observations for customer firms in either the treatment or control group. I(Post Merger of Supplier) is an indicator equal to one in the years following a merger deal involving the customer's supplier. I(Treated [Successful Merger]) equals one for customer firms whose original supplier was acquired in a successful merger, and the customer subsequently forms a supply relationship with the acquirer.

Panel A: Sample Construction

Treated Group: Successful Mergers	
Number of Total Successful Mergers (SDC) (2000 – 2022)	3,834
Number of Total Supply Chain Relationships (2003 – 2022)	73,447
(of which) Old Supply Chain Terminated due to Supplier Merger	1,779
(of which) Supply Chain Switches to Old Supplier's Acquirer as New Supplier	398
(of which) New Supplier has Climate Patent Ratio (Past 3 Years) Larger than 5%	33 (Final Treated Group)
Control Group: Failed Mergers	
Number of Total Failed Mergers (SDC) (2000 – 2022)	639
Number of Total Supply Chain Relationships (2003 – 2022)	73,447
(of which) Supplier was Target in Unsuccessful Merger Bid	1,290
(of which) Old Supply Chain Is Not Terminated	864
(of which) Bidder in Failed Merger has Climate Patent Ratio (Past 3 Years) Larger than 5%	169 (Final Control Group)

Panel B: Diff-in-Diff Estimate

Customer's Emissions	(1) Scope 1 Total	(2) Scope 1 Intensity	(3) Scope 2 Total	(4) Scope 2 Intensity
I(Post Merger of Supplier)	-0.158	0.267	-1.323**	-1.022*
	(0.821)	(0.766)	(0.668)	(0.614)
I(Treated [Successful Merger]) x I(Post Merger of Supplier)	-3.078**	-3.063***	-1.513	-1.529*
	(1.207)	(1.166)	(1.001)	(0.920)
Customer's Control	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
N	948	938	948	938
adj. R^2	0.931	0.892	0.933	0.712

Table 9. Discrete Choice Model Regarding the Choice of Suppliers by Customers

This table estimates a McFadden discrete choice model of the selection of potential suppliers by each customer firm. For each customer firm with at least one supplier in a given year, the set of alternatives includes (i) suppliers that are selected by the given customer and (ii) suppliers with similar products (using Hoberg and Phillips (2016)'s text-based network industry classification (TNIC)) that are not selected by the given customer. The regression sample is at the level of customer × potential supplier × year. We use OLS to estimate the model. The dependent variable is a dummy that equals one if the customer firm selects the supplier to establish the supply chain relationship in year t. Climate Patent Ratio [t-1] is measured for the supplier in year $t-1$. Environmental Score [t] is the score of the customer. Customer (supplier) control variables include customer (supplier) firm size, Tobin's q, ROA, PPE, book leverage, and sales growth. Robust standard errors are clustered at the customer firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Discrete Choice Model Estimated by OLS				I(Supplier-Customer Match)					
Supplier's Climate Patent Ratio [t-1]	0.021***		0.015***	0.017		-0.098***	-0.079***		
	(0.005)		(0.004)	(0.015)		(0.027)	(0.030)		
Supplier's Num General Patents [t-1]	0.003***		0.003***	0.003***		0.016***	0.010***		
	(0.001)		(0.000)	(0.000)		(0.002)	(0.002)		
Supplier's Climate Patent Ratio [t-1] × I(Post 2010)		0.026***			0.018***			-0.119***	-0.095***
		(0.005)			(0.005)			(0.028)	(0.032)
Supplier's Climate Patent Ratio [t-1] × I(Before 2010)		0.004			0.002			0.008	0.012
		(0.005)			(0.005)			(0.047)	(0.053)
Supplier's Num General Patents [t-1] × I(Post 2010)		0.003***			0.004***			0.018***	0.011***
		(0.000)			(0.000)			(0.002)	(0.002)
Supplier's Num General Patents [t-1] × I(Before 2010)		0.004***			0.003***			0.008*	0.007***
		(0.001)			(0.001)			(0.004)	(0.002)
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t]			0.013***	0.016***					
			(0.004)	(0.006)					
Supplier's Num General Patents [t-1] × Customer's Environmental Score [t]			-0.001	-0.001					
			(0.001)	(0.001)					
Supplier's Climate Patent Ratio [t-1] × Customer's Social Score [t]				-0.003					
				(0.006)					
Supplier's Climate Patent Ratio [t-1] × Customer's Governance Score [t]				0.000					
				(0.004)					
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t] × I(Post 2010)					0.017***				
					(0.005)				
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t] × I(Before 2010)					0.003				
					(0.005)				
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Total) [t]						0.008***			
						(0.002)			
Supplier's Climate Patent Ratio [t-1] × Customer's Firm Size [t]						0.002	0.006*		
						(0.004)	(0.003)		
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Intensity) [t]							0.011***		
							(0.002)		
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Total) [t] × I(Post 2010)								0.011***	
								(0.003)	

Continued on next page

Table 9 – continued from previous page

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Total) [t] × I(Before 2010)								0.004	
								(0.003)	
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Intensity) [t] × I(Post 2010)									0.014***
									(0.002)
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Intensity) [t] × I(Before 2010)									0.005*
									(0.002)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier NAICS-4 F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1696323	1696323	1696323	1668520	1696323	1466725	1466725	1466725	1466725
Adjusted R^2	0.065	0.065	0.065	0.065	0.065	0.069	0.069	0.069	0.069

Table 10. Climate Patent Ratio and New Customer Firms

This table examines the association between the number of new customer firms that purchase goods or services from a given supplier and the supplier's climate patent ratio. The regression sample includes all CRSP-Compustat firms with at least one new customer establishing supplier-customer relationships with the firm from 2005 to 2021. Supplier firms in the financial, retail, and wholesale industries are excluded from the sample. The dependent variable is the number of new customer firms that establish supplier-customer relationships with firm i in year t. The main independent variable, $\textit{Climate Patent Ratio}_{t-1}$, is the ratio of new climate patents (Y02) newly invented by the firm in year $t-1$. Post-2010 and Before-2010 are dummies equal to 1 after and before 2010, respectively. Number of General Patents measures the total number of new patents invented by the firm in year $t-1$. In Panel A, we conduct a sample split every year for all new customer firms by the annual median environmental score. Then, we define two new dependent variables: the number of new customers with high (low) environmental scores. Panels B and C conduct similar sample splits but use the environmental supply chain policy dummy and the total GHG emissions (Scope 1+2), respectively. The environmental supply chain (ESC) policy dummy equals one if a customer firm considers the environmental dimension in selecting potential suppliers. Panel D explores possible customer departures subsequent to climate innovation by their suppliers. The dependent variable is the number of firms that cease purchasing products or services from the specified suppliers. These customers are divided into two groups based on their environmental scores: those with high scores and those with low scores. Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Industry (NAICS 4-digit) fixed effects are included in columns (1) to (3), and firm F.E. are added in columns (4) to (6). Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A: Customer Firms Split by Environmental Score

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of New Customer Firms (Attracted by the Supplier)					
Customer Type	All Firms	High Environmental Score	Low Environmental Score	All Firms	High Environmental Score	Low Environmental Score
Supplier's ···						
Climate Patent Ratio [t-1] × Post 2010	0.110***	0.129***	-0.024	0.098**	0.105***	0.007
	(0.038)	(0.033)	(0.026)	(0.047)	(0.038)	(0.034)
Climate Patent Ratio [t-1] × Before 2010	-0.022	-0.014	-0.008	-0.035	-0.055	0.045
	(0.036)	(0.029)	(0.022)	(0.053)	(0.042)	(0.032)
Number of General Patents [t-1]	0.016***	0.009***	0.013***	0.015*	0.008	0.012*
	(0.005)	(0.003)	(0.004)	(0.008)	(0.006)	(0.006)
Firm Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Industry F.E.	Y	Y	Y			
Firm F.E.				Y	Y	Y
Num. Obs.	30471	30471	30471	30285	30285	30285
Adjusted R^2	0.218	0.147	0.176	0.275	0.202	0.234

Table 10 – continued from previous page

Panel B: Customer Firms Split by Environmental Supply Chain (ESC) Policy

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of New Customer Firms (Attracted by the Supplier)					
Customer Type	All Firms	ESC Management = Y	ESC Management = N	All Firms	ESC Management = Y	ESC Management = N
Supplier's ⋯						
Climate Patent Ratio [t-1] × Post 2010	0.058	0.072**	-0.030	0.048	0.082**	-0.036
	(0.036)	(0.032)	(0.023)	(0.046)	(0.041)	(0.030)
Climate Patent Ratio [t-1] × Before 2010	-0.025	-0.014	-0.007	-0.040	-0.047	0.023
	(0.035)	(0.026)	(0.026)	(0.051)	(0.037)	(0.033)
Number of General Patents [t-1]	0.016***	0.009***	0.013***	0.012	0.010*	0.009*
	(0.004)	(0.003)	(0.003)	(0.008)	(0.006)	(0.005)
Firm Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Industry F.E.	Y	Y	Y			
Firm F.E.				Y	Y	Y
Num. Obs.	29827	29827	29827	29648	29648	29648
Adjusted R^2	0.215	0.165	0.155	0.262	0.208	0.206

Panel C: Customer Firms Split by GHG Emissions (Scope 1+2)

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of New Customer Firms (Attracted by the Supplier)					
Customer Type	All Firms	High Total Emission	Low Total Emission	All Firms	High Total Emission	Low Total Emission
Supplier's ⋯						
Climate Patent Ratio [t-1] × Post 2010	0.081**	0.176***	-0.117***	0.037	0.093**	-0.070**
	(0.039)	(0.038)	(0.031)	(0.049)	(0.044)	(0.034)
Climate Patent Ratio [t-1] × Before 2010	-0.001	-0.030	0.018	-0.019	-0.084*	0.058
	(0.046)	(0.035)	(0.034)	(0.062)	(0.044)	(0.050)
Number of General Patents [t-1]	0.044***	0.017***	0.047***	0.042***	0.020***	0.042***
	(0.006)	(0.004)	(0.005)	(0.010)	(0.007)	(0.009)
Firm Controls	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Industry F.E.	Y	Y	Y			
Firm F.E.				Y	Y	Y
Num. Obs.	29495	29495	29495	29275	29275	29275
Adjusted R^2	0.279	0.189	0.253	0.346	0.259	0.333

Panel D: Existing Customers' Possible Departure

	(1)	(2)	(3)
	Number of Departures of Existing Customers		
Customer Split by		Environmental Score	
	All Customers	High E-Score	Low E-Score
Supplier's ⋯			
Climate Patent Ratio (t-1) × Post 2010	0.004	0.006	-0.019
	(0.031)	(0.024)	(0.022)
Climate Patent Ratio (t-1) × Before 2010	0.016	0.012	0.008
	(0.029)	(0.022)	(0.019)
Firm Controls	Y	Y	Y
Year F.E.	Y	Y	Y
Firm F.E.	Y	Y	Y
Num. Obs.	52014	52014	52014
Adjusted R^2	0.351	0.240	0.280

Table 11. Climate Patent Ratio and New Customer Firms (Examiner Leniency as Instrument)

This table examines the association between the number of new customer firms that purchase goods or services from a given supplier and the supplier's climate patent ratio in a 2SLS-regression setup. In each panel, columns (1) and (2) show the 1st stage regressions, and columns (3) – (8) tabulate the 2nd stage regressions. We use the difference of leniency between examiners who assess climate patent and non-climate patent applications to instrument the key independent variable, climate patent ratio. Specifically, the Examiner Leniency Diff. is defined as,

$$\text{Examiner's Leniency Difference}_{i,t} = \frac{1}{N_{clim}} \sum_{p \in \text{Clim}}^{N_{clim}} [\text{Examiner Leniency}_{p,e}] - \frac{1}{N_{non\text{-}clim}} \sum_{p \in \text{Non-Clim}}^{N_{non\text{-}clim}} [\text{Examiner Leniency}_{p,e}] \tag{8}$$

where N_{clim} ($N_{non\text{-}clim}$) is the number of climate (non-climate) patent applications submitted by firm i and receive decisions (granting or rejection) from the USPTO in year t. Examiner $\text{Leniency}_{p,e}$ is the leniency of the examiner e who reviews the given patent application p. Specifically, it is constructed as

$$\text{Examiner Leniency}_{p,e} = \frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1} - \frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1} \tag{9}$$

$\frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1}$ is examiner e's all-time granting ratio in her career in the USPTO, excluding the focal application p (the one out in the standard leave-one-out method). When calculating an examiner's leniency, we use all patent applications, including climate and non-climate patent applications. We require each examiner to examine at least ten applications in the dataset. The same method applies to calculating the average granting ratio of the art unit to which the application is assigned and to which examiner e belongs: $\frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1}$. Hence, our leniency measure is a relative leniency measure within an art unit.

In Panel A, we conduct a sample split every year for all new customer firms by the annual median environmental score. Then, we define two new dependent variables: the number of new customers with high (low) environmental scores. Panel A (columns (4) – (6)) and B conduct similar sample splits but use the environmental supply chain policy dummy and the total GHG emissions (Scope 1+2), respectively. The environmental supply chain (ESC) policy dummy equals one if a customer firm considers the environmental dimension in selecting potential suppliers. Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Table 11 – continued from previous page

Panel A: Customer Firms Split by Environmental Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First Stage		Second Stage					
	Climate Patent Ratio		Number of New Customer Firms					
			Split by Environmental Score			Split by Supply Chain Policy		
			All Firms	High	Low	All Firms	Yes	No
Examiner's Leniency Difference	0.165***	0.172***						
(Instrumental Variable)	(0.033)	(0.028)						
Climate Patent App Ratio		0.961***						
		(0.033)						
Climate $\widehat{Patent}$ Ratio × Post 2010			0.228**	0.354***	-0.054	0.139	0.261***	-0.117
(Instrumented by Examiner's Leniency Difference × Post 2010)			(0.110)	(0.092)	(0.080)	(0.112)	(0.099)	(0.071)
Climate $\widehat{Patent}$ Ratio × Before 2010			0.215	0.145	0.126	0.192	0.112	0.131
(Instrumented by Examiner's Leniency Difference × Before 2010)			(0.168)	(0.124)	(0.122)	(0.167)	(0.122)	(0.131)
Climate Patent App Ratio × Post 2010			-0.065	-0.066	-0.069	-0.053	0.013	-0.113
			(0.127)	(0.113)	(0.095)	(0.124)	(0.108)	(0.086)
Climate Patent App Ratio × Before 2010			0.010	-0.081	0.114	-0.000	-0.047	0.091
			(0.126)	(0.106)	(0.102)	(0.125)	(0.105)	(0.089)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E. and Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Weak Instrument F Test	62.091	63.930						
Num. Obs.	3497	3497	3318	3318	3318	3265	3265	3265

Panel B: Customer Firms Split by CO2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	First Stage		Second Stage					
	Climate Patent Ratio		Number of New Customer Firms					
			Split by Total Emissions			Split by Emission Intensity		
			All Firms	High	Low	All Firms	High	Low
Examiner's Leniency Difference	0.165***	0.172***						
(Instrumental Variable)	(0.033)	(0.028)						
Climate Patent App Ratio		0.961***						
		(0.033)						
Climate $\widehat{Patent}$ Ratio × Post 2010			0.203*	0.248***	-0.010	0.203*	0.150*	0.065
(Instrumented by Examiner's Leniency Difference × Post 2010)			(0.116)	(0.088)	(0.083)	(0.116)	(0.087)	(0.087)
Climate $\widehat{Patent}$ Ratio × Before 2010			0.184	0.147	0.079	0.184	0.154	0.035
(Instrumented by Examiner's Leniency Difference × Before 2010)			(0.144)	(0.098)	(0.109)	(0.144)	(0.104)	(0.099)
Climate Patent App Ratio × Post 2010			-0.056	0.011	-0.085	-0.056	0.025	-0.069
			(0.134)	(0.117)	(0.083)	(0.134)	(0.108)	(0.090)
Climate Patent App Ratio × Before 2010			-0.050	-0.088	0.059	-0.050	-0.029	0.025
			(0.127)	(0.106)	(0.085)	(0.127)	(0.104)	(0.092)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E. and Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Weak Instrument F Test	62.091	63.930						
Num. Obs.	3497	3497	2995	2995	2995	2995	2995	2995

Table 12. Climate Innovators and Operating Performance

This table examines the impact of climate innovation on firms' operating performance subsequent to their climate innovation effort, measured by the climate patent ratio in year t-1. The dependent variables are: sales, return on assets (ROA), and mark-ups (or profit margin). Mark-up is defined as is defined as (total sales − cost of goods sold)/(total sales). The firm-level control variables include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Standard errors are clustered at the firm level. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels respectively.

Panel A: Operating Performance of Climate Innovators (Sales and Profits)

	(1)	(2)	(3)
	Operating Performance		
	Ln(Sales)	ROA	Profit
Supplier's ⋯			
Climate Patent Ratio (t-1) × Post 2010	0.080**	0.004	0.095
	(0.038)	(0.009)	(0.191)
Climate Patent Ratio (t-1) × Before 2010	-0.045	-0.022*	-0.114*
	(0.049)	(0.013)	(0.068)
Firm Controls	Y	Y	Y
Year F.E.	Y	Y	Y
Firm F.E.	Y	Y	Y
Num. Obs.	62776	63062	62776
Adjusted R^2	0.961	0.736	0.546

Panel B: Sales of Customers Who Choose Climate Tech Suppliers

	(1)	(2)	(3)
	Operating Performance		
	Ln(Sales) t+1	Ln(Sales) t+2	Ln(Sales) t+3
I[New Supplier with Climate Patents]	-0.008	0.008	-0.003
	(0.009)	(0.010)	(0.013)
I[Old Supplier with Climate Patents]	-0.016	-0.020	-0.024
	(0.016)	(0.019)	(0.023)
Firm Controls	Y	Y	Y
Industry × Year F.E.	Y	Y	Y
Firm F.E.	Y	Y	Y
Num. Obs.	14175	12076	10192
Adjusted R^2	0.982	0.979	0.978

Panel C: ROA of Customers Who Choose Climate Tech Suppliers

	(1)	(2)	(3)
	Operating Performance		
	ROA t+1	ROA t+2	ROA t+3
I[New Supplier with Climate Patents]	-0.003	0.001	-0.002
	(0.002)	(0.002)	(0.003)
I[Old Supplier with Climate Patents]	-0.000	-0.001	0.002
	(0.003)	(0.003)	(0.004)
Firm Controls	Y	Y	Y
Industry × Year F.E.	Y	Y	Y
Firm F.E.	Y	Y	Y
Num. Obs.	14203	12112	10210
Adjusted R^2	0.842	0.830	0.819

Internet Appendix for

"Climate Innovation and Carbon Emissions: Evidence from Supply Chain Networks"

Results and Material Not Included in the Paper

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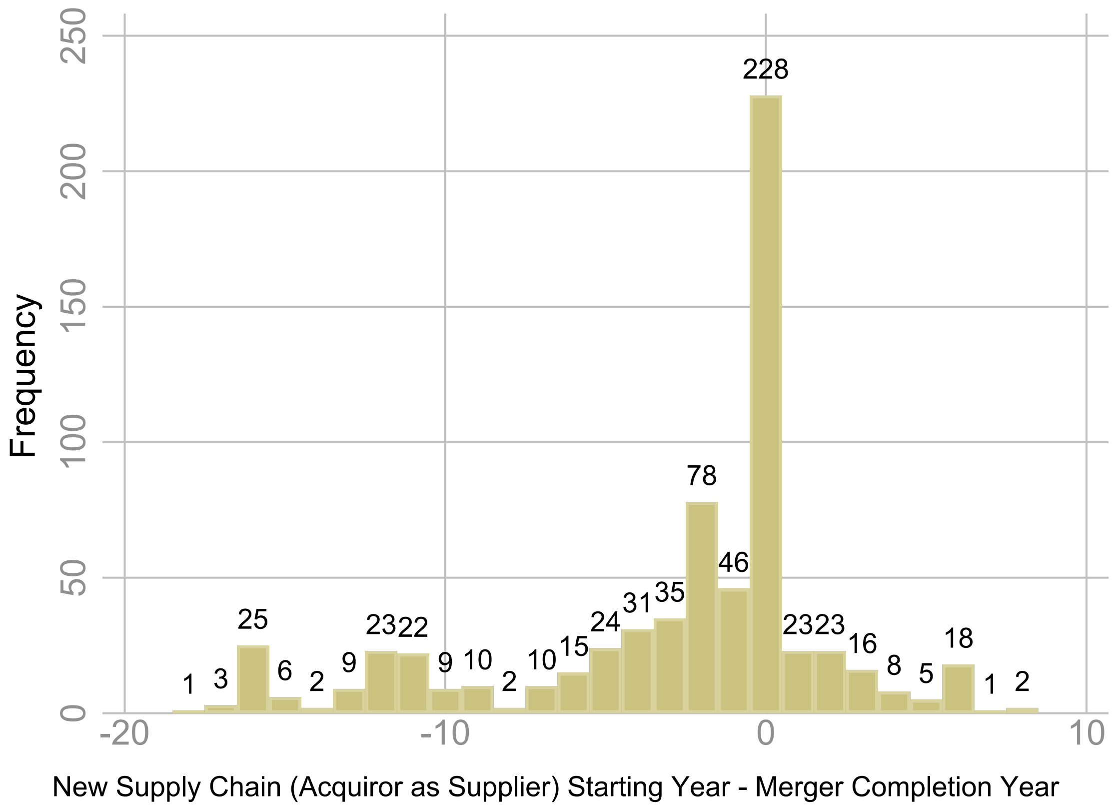
Appendices

Figure A1. Timing of Supply Chain Terminations Around Merger Completion

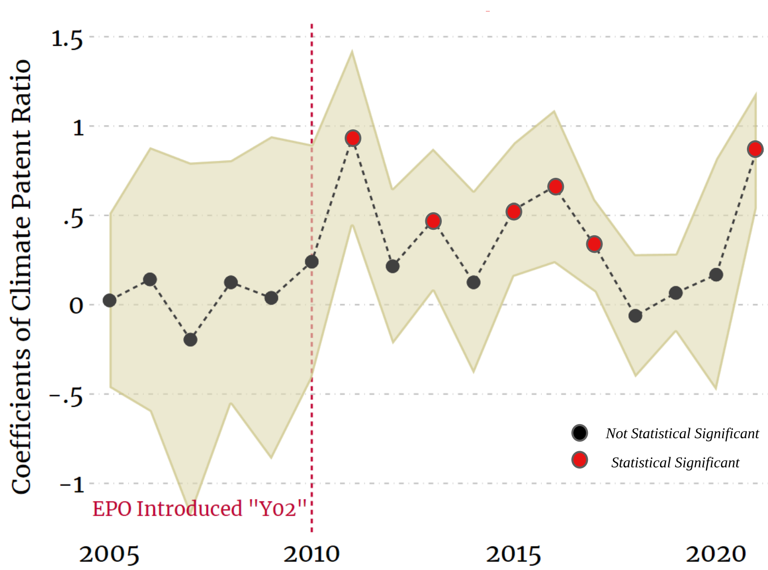
This figure plots the distribution of termination years for supplier–customer relationships in which the supplier is the target of a merger bid. The horizontal axis denotes the number of years relative to the merger completion year (Year 0). The vertical axis shows the number of terminated relationships. The figure highlights that terminations are most concentrated in Year 0, the year the merger is completed. ***Note:*** Negative number means that the supply chain stops before the merger deal.

Figure A2. Timing of New Supply Chain Formation Relative to Merger Completion



This figure plots the distribution of the starting year of new supplier–customer relationships in which the new supplier is the acquirer of a successfully merged target. The horizontal axis shows the number of years relative to the merger completion year (Year 0), and the vertical axis reports the number of new supply chain relationships formed in each year. The figure highlights that new supplier relationships are most frequently initiated in Year 0, the year the merger is completed. Note: Negative values indicate that the new supply chain was formed prior to the merger's effective year.

Figure A3. Supplier's Climate Patent and New-Attracted Customer Firms — **Poisson Regression**

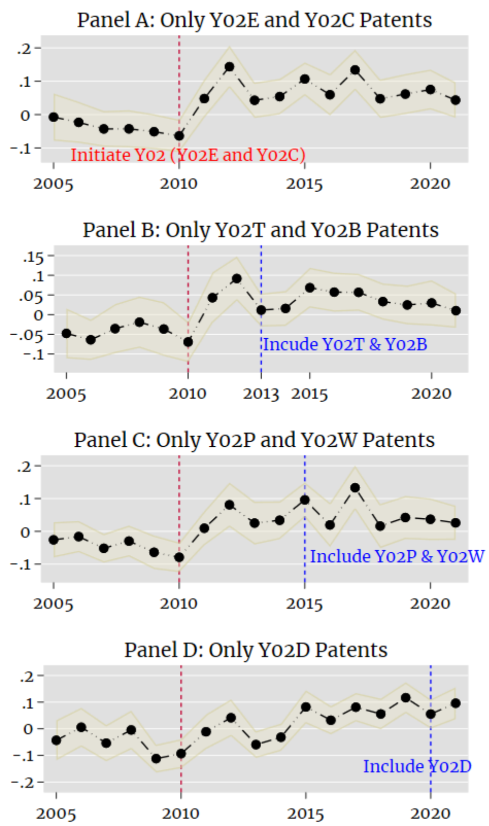


This figure examines the relationship between the climate patent ratio and the number of new customers attracted by each supplier firm. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t\Big) + \\ \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (10)$$

Where $Num\_New\_Customer\_Firms_{i,t}$ denotes the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. We conduct **Poisson regression** instead of using the natural logarithm of $(1 + x)$. The variable $Clim\_Patent\_Ratio_{i,\mathbf{t\text{-}1}}$ represents the ratio of climate-related patents (Y02) newly granted to the firm to all patents granted to the same firm in year $t - 1$. The regression model includes control variables for firm-specific factors, such as firm size, Tobin's q, cash, book leverage, ROA, capital expenditure, sales growth, and the count of existing customers. These variables are measured in year $t - 1$. Additionally, industry (NAICS 4-digit) $\times$ year fixed effects are included. Standard errors are clustered at the firm level, and the confidence intervals depicted in the figure denote a 90% confidence level.

Figure A4. Staggered Introduction of Climate Patent "Y02" Categories



This figure studies the impact of the staggered introduction of EPO climate patents Y02 tags on the acquisition of new customer firms. The regression sample is at the supplier firm × year level. In each panel, we run the following regression,

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \left(\text{Num\_Clim\_Pats}_{i,\mathbf{t\text{-}1}}^{SUBSET} \times I(\text{Year})_t \right) + \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (11)$$

Where $Num\_New\_Customer\_Firms_{i,t}$ denotes the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. The equation is the same as the equation in Figure 4 except that (i) we use the number of climate patents as the main explanatory variable; (ii) in each panel, only a subset of climate patents are counted. In Panel A, Y02C and Y02E are counted. In Panel B, Y02B and Y02T are counted. In Panel C, Y02P and Y02W are counted. The regression model contains control variables for firm-specific factors, such as firm size, Tobin's q, cash, book leverage, ROA, capital expenditure, sales growth, and the count of existing customers. These variables are measured in year $t-1$. Additionally, industry (NAICS 4-digit) × year fixed effects are included. Standard errors are clustered at the firm level, and the confidence intervals depicted in the figure denote a 90% confidence level.

Table A1. Number of Climate-related Patents (Y02) by Patent Application Year

This table presents the annual number of climate-related patents filed by CRSP-Compustat firms from 2000 to 2020 (sorted by patent filing (application) year). To compile this data, we combined updated patent data from Kogan et al. (2017) with recent patent data from PatentsView.org, covering the granting years 2020 to 2022. To identify climate patents, we used the "Y02" tag in the CPC codes of each patent, excluding Y02A. Climate patents were further categorized into climate process and product patents, following the approach outlined in Bena et al. (2022) and Ma (2022) for general patents. Specifically, a patent is classified as a process patent if its first claim (typically the most important claim) begins with phrases such as "A process of," "A method of," "A method for," and so on.

Panel A: Climate Patent by Year

	Full Sample	By Process and Product		By Industries and Sectors						
Patents by (Filing) Year	Total Climate Related Patents	Climate Process Patents	Climate Product Patents	Buildings Y02B	GHG Storage Y02C	ICT Y02D	Energy Y02E	Production Y02P	Transportation Y02T	Wastewater Y02W
2000	3199	966	2233	197	44	471	978	844	937	62
2001	4164	1272	2892	289	61	612	1380	1110	1115	108
2002	4587	1428	3159	329	60	630	1412	1219	1366	97
2003	4421	1352	3069	412	39	635	1290	1091	1348	107
2004	4436	1311	3125	367	34	734	1267	920	1467	96
2005	4562	1256	3306	429	35	831	1353	876	1487	78
2006	4643	1373	3270	369	40	859	1323	882	1614	94
2007	5041	1567	3474	469	43	1063	1419	953	1635	72
2008	5476	1691	3785	426	60	1286	1615	849	1818	64
2009	5058	1624	3434	448	54	1101	1612	786	1658	69
2010	5773	1853	3920	571	57	1288	1862	910	1818	79
2011	6486	2096	4390	646	70	1542	1946	987	2168	60
2012	7235	2490	4745	663	61	2085	1899	957	2390	93
2013	6968	2475	4493	684	80	2136	1732	914	2216	101
2014	6746	2314	4432	663	61	1837	1631	1008	2367	74
2015	7464	2192	5272	663	100	1892	1778	1154	2800	67
2016	7290	2125	5165	694	82	1923	1612	1161	2701	86
2017	7216	2028	5188	664	66	1853	1737	1185	2615	43
2018	6355	1650	4705	594	50	1620	1609	1030	2282	45
2019	5331	1429	3902	502	42	1461	1357	751	1890	39
2020	2400	644	1756	235	12	750	466	309	824	38
Total	114851	35136	79715	10314	1151	26609	31278	19896	38516	1572

Table A1 – continued from previous page

Panel B: Process and Product Patents by CPC Y02 Categories

Patents by	Buildings Y02B				ICT Y02D				Energy Y02E				Waste Y02W			
(Filing) Year	Process Patents		Product Patents		Process Patents		Product Patents		Process Patents		Product Patents		Process Patents		Product Patents	
2000	13	6.34%	192	93.66%	190	39.75%	288	60.25%	222	21.10%	830	78.90%	34	51.52%	32	48.48%
2001	43	14.14%	261	85.86%	270	42.93%	359	57.07%	345	22.98%	1156	77.02%	58	49.57%	59	50.43%
2002	56	16.62%	281	83.38%	272	42.24%	372	57.76%	314	21.12%	1173	78.88%	51	48.11%	55	51.89%
2003	63	14.79%	363	85.21%	284	43.83%	364	56.17%	308	22.29%	1074	77.71%	53	47.75%	58	52.25%
2004	59	15.25%	328	84.75%	320	42.61%	431	57.39%	257	19.24%	1079	80.76%	55	56.12%	43	43.88%
2005	59	13.05%	393	86.95%	351	41.39%	497	58.61%	290	20.45%	1128	79.55%	32	41.03%	46	58.97%
2006	58	14.50%	342	85.50%	408	46.58%	468	53.42%	301	21.69%	1087	78.31%	47	48.96%	49	51.04%
2007	81	16.46%	411	83.54%	554	50.92%	534	49.08%	325	21.87%	1161	78.13%	42	55.26%	34	44.74%
2008	94	20.39%	367	79.61%	662	50.27%	655	49.73%	400	23.56%	1298	76.44%	44	61.97%	27	38.03%
2009	94	19.50%	388	80.50%	565	50.04%	564	49.96%	453	26.77%	1239	73.23%	33	48.53%	35	51.47%
2010	103	16.64%	516	83.36%	700	52.59%	631	47.41%	530	27.10%	1426	72.90%	46	58.23%	33	41.77%
2011	150	21.22%	557	78.78%	754	47.04%	849	52.96%	580	28.03%	1489	71.97%	41	58.57%	29	41.43%
2012	161	21.96%	572	78.04%	1098	50.93%	1058	49.07%	539	26.79%	1473	73.21%	52	52.53%	47	47.47%
2013	179	22.69%	610	77.31%	1086	48.12%	1171	51.88%	527	28.00%	1355	72.00%	54	54.55%	45	45.45%
2014	183	21.71%	660	78.29%	981	49.65%	995	50.35%	477	27.10%	1283	72.90%	57	70.37%	24	29.63%
2015	163	19.93%	655	80.07%	920	46.25%	1069	53.75%	468	24.48%	1444	75.52%	34	52.31%	31	47.69%
2016	146	18.43%	646	81.57%	816	43.40%	1064	56.60%	388	22.93%	1304	77.07%	39	42.39%	53	57.61%
2017	144	19.23%	605	80.77%	685	41.44%	968	58.56%	367	22.71%	1249	77.29%	18	48.65%	19	51.35%
2018	104	16.88%	512	83.12%	478	40.00%	717	60.00%	217	20.26%	854	79.74%	11	36.67%	19	63.33%
2019	55	15.45%	301	84.55%	292	43.98%	372	56.02%	86	24.23%	269	75.77%	9	47.37%	10	52.63%
2020	14	28.00%	36	72.00%	56	47.86%	61	52.14%	7	13.21%	46	86.79%	0	0.00%	10	100.00%
Total	2022	18.35%	8996	81.65%	11742	46.54%	13487	53.46%	7401	24.02%	23417	75.98%	810	51.66%	758	48.34%

Patents by	Production Y02P				Transportation Y02T				GHG Storage Y02C			
(Filing) Year	Process Patents		Product Patents		Process Patents		Product Patents		Process Patents		Product Patents	
2000	364	41.36%	516	58.64%	249	25.46%	729	74.54%	21	46.67%	24	53.33%
2001	473	40.53%	694	59.47%	271	23.20%	897	76.80%	41	66.13%	21	33.87%
2002	553	43.61%	715	56.39%	340	24.39%	1054	75.61%	35	53.85%	30	46.15%
2003	507	44.24%	639	55.76%	312	22.91%	1050	77.09%	16	37.21%	27	62.79%
2004	436	45.51%	522	54.49%	335	22.62%	1146	77.38%	19	46.34%	22	53.66%
2005	356	38.61%	566	61.39%	331	21.86%	1183	78.14%	12	34.29%	23	65.71%
2006	402	43.79%	516	56.21%	337	20.67%	1293	79.33%	20	50.00%	20	50.00%
2007	415	41.96%	574	58.04%	321	19.44%	1330	80.56%	27	62.79%	16	37.21%
2008	390	43.48%	507	56.52%	316	17.25%	1516	82.75%	32	52.46%	29	47.54%
2009	386	46.23%	449	53.77%	353	21.09%	1321	78.91%	32	57.14%	24	42.86%
2010	425	44.32%	534	55.68%	374	20.40%	1459	79.60%	27	42.86%	36	57.14%
2011	475	46.07%	556	53.93%	452	20.64%	1738	79.36%	29	39.73%	44	60.27%
2012	435	42.86%	580	57.14%	556	23.04%	1857	76.96%	29	43.94%	37	56.06%
2013	427	43.71%	550	56.29%	590	26.20%	1662	73.80%	43	48.86%	45	51.14%
2014	469	43.51%	609	56.49%	585	24.39%	1814	75.61%	39	57.35%	29	42.65%
2015	512	42.00%	707	58.00%	480	17.18%	2314	82.82%	49	43.36%	64	56.64%
2016	431	37.03%	733	62.97%	501	18.39%	2224	81.61%	38	40.86%	55	59.14%
2017	408	39.73%	619	60.27%	465	17.97%	2123	82.03%	21	30.00%	49	70.00%
2018	232	34.63%	438	65.37%	216	13.87%	1341	86.13%	12	38.71%	19	61.29%
2019	95	39.26%	147	60.74%	73	14.69%	424	85.31%	4	30.77%	9	69.23%
2020	13	29.55%	31	70.45%	3	6.98%	40	93.02%	0	0.00%	2	100.00%
Total	8204	42.28%	11202	57.72%	7460	20.74%	28515	79.26%	546	46.63%	625	53.37%

Table A2. Additional Summary Statistics

This table presents supplementary summary statistics. In Panel A, we present pair-wise correlations between environmental ratings and carbon emissions. The intensity of carbon emissions is calculated by dividing total emissions by total sales. In Panel B, we offer summary statistics for the sample of climate patent applications that forms the basis of our 2SLS regressions in Table 11.

Panel A: Pairwise Correlations among New Customer's Characteristics

Pair-wise Correlation

	Environmental Score	ESC Management	Industry Adjusted GHG Emission Total	Industry Adjusted GHG Emission Intensity
Environmental Score	1.000			
ESC Management Score	0.639	1.000		
Industry Adjusted GHG Emissions Total	0.159	0.119	1.000	
Industry Adjusted GHG Emissions Intensity	0.029	0.015	0.444	1.000

Panel B: Compustat Sample of Firms With At Least One Climate Patent Application

Variable	Mean	p25	p50	p75	SD	N
Number of New Customer Firms	0.477	0.000	0.000	0.693	0.664	4,046
Number of New Customer Firms (High E-score)	0.277	0.000	0.000	0.693	0.499	4,046
Number of New Customer Firms (Low E-score)	0.287	0.000	0.000	0.693	0.496	4,046
Number of Existing Customer Firms	1.824	1.099	1.946	2.639	1.060	4,046
Climate Patent Ratio	0.184	0.022	0.071	0.211	0.262	4,010
Climate Patent App. Ratio	0.188	0.034	0.083	0.222	0.253	4,046
Examiner's Leniency Diff.	-0.006	-0.049	0.000	0.046	0.105	3,840
Firm Size	8.294	6.746	8.375	9.892	2.185	4,045
Tobin's Q	2.186	1.308	1.749	2.556	1.442	3,686
Cash	0.218	0.073	0.157	0.315	0.190	4,042
Book Leverage	0.346	0.125	0.319	0.503	0.279	3,972
ROA	0.103	0.075	0.129	0.181	0.161	3,981
CAPX	0.042	0.018	0.031	0.054	0.039	3,997
Sales Growth	0.074	-0.041	0.046	0.144	0.275	3,975

Table A3. Robustness Check for Table 3 (**Number of Climate Patents**)

This table presents the robustness check for Table 3, where we replace the suppliers' climate patent ratio with the number of climate patents as the main explanatory variable. The sample used in the regressions follows Table 2, Panel A. Each observation in the customer sample represents a firm-year observation, with at least one supplier firm selling products or services to the given firm in that specific year. We only include supplier-customer relationships with non-missing sales information. Customer firms in the financial, retail, and wholesale sectors are excluded from the sample. Additionally, firms without CO2 emission information from Trucost are also excluded. In Panel A (Panel B), the dependent variable is the change in Scope 1 (Scope 2) CO2 emissions from year t to $t+k$. Total emissions is represented by the natural logarithm of CO2 emissions in tonnes, and emissions intensity is calculated as the natural logarithm of total emissions divided by output. The main independent variable, Supplier's Climate Patent Number [t], is the weighted number of climate patents held by all suppliers selling products or services to a given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent number is calculated as the natural logarithm of one plus the number of new climate patents invented in year t. Firm controls include firm size, Tobin's Q, cash, book leverage, return on assets (ROA), capital expenditure, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) × year fixed effects. Standard errors are clustered at the firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Scope 1 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Number [t]	-2.059	-2.032	-6.387**	-6.153**	-9.701**	-9.603**	-12.563**	-12.041**	-12.238**	-13.178**
	(1.574)	(1.545)	(2.766)	(2.508)	(3.997)	(3.795)	(4.962)	(4.770)	(5.562)	(5.627)
Supplier's General Patent Number [t]	0.599	0.241	3.576	3.529	5.017	5.336	5.722	5.471	4.770	5.003
	(1.551)	(1.412)	(2.713)	(2.363)	(4.204)	(3.874)	(5.449)	(5.122)	(6.797)	(6.512)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.109	0.077	0.168	0.123	0.204	0.143	0.242	0.196	0.324	0.256

Panel B: Scope 2 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 2 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Number [t]	-2.887*	-2.600**	-6.396**	-5.992***	-7.506**	-6.945***	-8.403*	-7.398**	-5.760	-5.867
	(1.514)	(1.293)	(2.508)	(1.911)	(3.347)	(2.520)	(4.378)	(3.253)	(5.427)	(3.765)
Supplier's General Patent Number [t]	1.982	1.323	4.254*	3.722*	4.898	4.673	4.941	3.861	0.730	0.565
	(1.439)	(1.249)	(2.490)	(2.095)	(3.505)	(2.850)	(4.536)	(3.693)	(5.384)	(4.519)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.110	0.079	0.165	0.121	0.202	0.142	0.239	0.192	0.323	0.254

Table A4. Robustness Check for Table 3 (**Measure Climate Patents in the Past 3 Years**)

This table provides robustness checks of the main results presented in Table 3. All key independent variables related to climate patents and general patents are constructed using the supplier's patents from years $t-2$, $t-1$, and t. Firm controls include firm size, Tobin's Q, cash, book leverage, return on assets (ROA), capital expenditures, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) $\times$ year fixed effects. To enhance readability, coefficients are multiplied by 100. Standard errors are clustered at the firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Scope 1 CO2 Emissions

Change of Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t-2, t-1, t]	-2.812**	-3.168***	-4.271*	-4.702**	-6.647**	-7.598***	-7.566**	-9.010***	-9.370***	-11.123***
	(1.320)	(1.161)	(2.314)	(1.895)	(2.638)	(2.034)	(3.175)	(2.665)	(3.599)	(3.332)
Supplier's Number of General Patent [t-2, t-1, t]	0.375	0.070	1.005	1.142	0.723	1.321	-0.740	0.351	-1.244	-0.788
	(1.128)	(1.075)	(2.184)	(1.935)	(3.199)	(2.793)	(4.109)	(3.626)	(4.980)	(4.742)
Customer's Climate Patent Ratio [t-2, t-1, t]	2.980**	2.337**	4.506**	3.627**	3.401	2.860	3.771	3.659	3.761	1.117
	(1.218)	(0.937)	(1.945)	(1.744)	(2.450)	(2.116)	(3.540)	(3.010)	(4.293)	(3.715)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.099	0.073	0.131	0.102	0.151	0.119	0.155	0.165	0.185	0.218

Panel B: Scope 2 CO2 Emissions

Change of Scope 2 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t-2, t-1, t]	-1.471	-1.292	-5.965*	-5.768**	-5.154	-5.633	-6.826	-7.778*	-6.345	-6.831
	(1.281)	(1.077)	(3.207)	(2.672)	(5.268)	(4.236)	(5.697)	(4.604)	(5.354)	(4.667)
Supplier's Number of General Patent [t-2, t-1, t]	0.813	0.142	2.275	1.757	1.558	1.714	0.990	1.492	-0.948	-0.660
	(1.302)	(1.064)	(2.027)	(1.623)	(2.825)	(2.124)	(3.767)	(2.890)	(4.786)	(3.862)
Customer's Climate Patent Ratio [t-2, t-1, t]	0.388	-1.109	1.891	0.289	3.829	2.034	4.573	4.216	8.671	5.858
	(1.252)	(1.060)	(3.151)	(2.377)	(4.158)	(3.638)	(5.938)	(5.343)	(6.987)	(5.945)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.098	0.071	0.132	0.104	0.153	0.121	0.157	0.167	0.182	0.210

Table A5. Climate Patents and Scope 3 Downstream Emissions

This table examines the relationship between firms' climate patent ratio and their Scope 3 downstream CO2 emissions. The sample consists of all firm-year observations with non-missing Scope 3 downstream emissions data in both the Trucost and CRSP-Compustat datasets. The dependent variable in this analysis is the Scope 3 downstream emissions in the subsequent three years. To control for firm-specific characteristics, we include several firm controls such as firm size, Tobin's Q, cash holdings, book leverage, return on assets (ROA), capital expenditure, sales growth, and property, plant, and equipment (PPE). To account for time-specific factors, all regressions incorporate firm and year fixed effects. Standard errors are clustered at the firm level to address potential heteroscedasticity. Statistical significance is indicated by *, **, and ***, representing significance at the 10%, 5%, and 1% levels, respectively.

Scope 3 Downstream Emissions	(1) t+1	(2)	(3) t+2	(4)	(5) t+3	(6)
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity
Climate Patent Ratio (Product)	1.785	2.139	3.169	2.627	-5.016*	-4.651*
	(2.235)	(2.187)	(2.737)	(2.807)	(2.639)	(2.616)
Climate Patent Ratio (Process)	3.270	2.682	2.119	1.861	1.989	1.292
	(2.474)	(2.460)	(2.385)	(2.397)	(1.819)	(1.927)
Num General Pat (Product)	8.567	9.289	-20.084**	-17.299**	3.283	1.827
	(6.878)	(6.806)	(7.790)	(7.357)	(12.051)	(11.752)
Num General Pat (Process)	-10.204	-8.613	5.135	2.007	-11.225	-12.360
	(6.432)	(6.180)	(7.810)	(7.099)	(9.081)	(8.797)
Firm F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
N	7229	7097	5900	5788	4715	4624
adj. R^2	0.946	0.920	0.943	0.917	0.931	0.901

Table A6. Supplier's Climate Patents and Customer's CO2 Emission Changes (Green vs. Grey Patents)

This table explores the role of the direction of technical change on customer's carbon emissions. The table classifies all climate patents into either "green" climate patents (renewable energy and its applications) and "grey/hybrid" climate patents (ex. energy efficient technology). The classification follows Aghion et al. (2016). The sample used in the regressions follows Table 2, Panel A. Each observation in the customer sample represents a firm-year observation with at least one supplier firm that sold products or services to the given firm in that specific year. We only include supplier-customer relationships with non-missing sales information. Customer firms in the financial, retail, and wholesale sectors are excluded from the sample. Additionally, firms without CO2 emission information from Trucost are also excluded. The dependent variable in Panel A (Panel B) is the change in Scope 1 (Scope 2) CO2 emissions from year t to $t+k$. Total emissions is represented by the natural logarithm of CO2 emissions in tons, and emission intensity is calculated as the natural logarithm of total emissions divided by output. The main independent variable, Supplier's Climate Patent Ratio [t], is the weighted climate patent ratio of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate patents newly invented divided by the total number of patents invented in year t. Firm controls include firm size, Tobin's q, cash, book leverage, return on assets (ROA), capital expenditures, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) × year fixed effects. To enhance readability, coefficients are multiplied by 100. Standard errors are clustered at the firm level. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: "Pure Green" Climate Patents

Change of Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-5.116**	-5.284***	-6.494**	-6.086**	-7.173**	-6.565**	-9.105**	-8.832*	-10.808**	-10.450**
	(2.027)	(1.986)	(2.959)	(3.039)	(3.248)	(3.286)	(4.054)	(4.565)	(4.662)	(4.619)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.099	0.073	0.131	0.102	0.151	0.119	0.155	0.165	0.185	0.218

Panel B: "Grey/Hybrid" Climate Patents

Change of Scope 1 CO2 Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-0.265	-0.658	-1.412	-2.186	-2.873	-4.780**	-2.684	-4.605**	-5.963*	-9.204***
	(0.963)	(1.016)	(1.582)	(1.394)	(2.291)	(1.954)	(2.426)	(2.073)	(3.268)	(3.317)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1804	1743	1782	1711	1625	1555	1473	1404	1327	1258
Adjusted R^2	0.098	0.071	0.132	0.104	0.153	0.121	0.157	0.167	0.182	0.210

Table A7. Supplier's Climate Innovation and Customer's Emissions (Examiner Busyness)

This table provides exogenous variation in the quality of climate patents. Panel A presents the regression sample, which includes all climate patents granted to CRSP-Compustat firms from 2001 to 2022. The measure of examiner busyness is defined as the total number of decisions (including allowances, non-final rejections, and final rejections) made by the examiner who evaluated the focal climate patent in the year the climate patent was granted. The examiner busyness measure is demeaned using the median busyness level for the corresponding art unit × year. In Panels B and C, we utilize the supplier–customer pair sample to conduct regressions. The examiner busyness measure is the average busyness of examiners for climate patents granted to the supplier. These patents are sorted by the application year. Fixed effects for the number of climate patents applied by suppliers and for supplier–customer pairs are consistently included. Standard errors are clustered at the customer-firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. For ease of interpretation, coefficients are multiplied by 100.

Panel A: Examiner's Busyness and Patent Citations

	(1)	(2)	(3)
Poisson Regression	Climate Patent Citation		
Examiner_Busyness	-4.063***	-2.090***	-1.670**
	(0.687)	(0.701)	(0.706)
KPSS Patent Value	25.921***	4.359**	4.670**
	(0.713)	(2.066)	(2.041)
Grant Year F.E.	Y	Y	Y
Firm F.E.	N	Y	Y
CPC (Patent Classification) F.E.	N	N	Y
Num. Obs.	108,442	108,084	108,084

Panel B: Supplier-Customer Pair Sample (Scope 1 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 1 Emission Total			Scope 1 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Examiner_Busyness (*Supplier's Climate Patents*)	0.711	1.776***	1.800**	0.435	1.236*	1.305*
	(0.603)	(0.682)	(0.738)	(0.586)	(0.664)	(0.721)
Num. Climate Patents F.E.	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	13132	11018	9072	12892	10884	8966
adj. R^2	0.969	0.970	0.970	0.951	0.953	0.954

Panel C: Supplier-Customer Pair Sample (Scope 2 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 2 Emission Total			Scope 2 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Examiner_Busyness (*Supplier's Climate Patents*)	0.320	1.367*	0.521	-0.140	0.629	0.177
	(0.651)	(0.715)	(0.748)	(0.549)	(0.607)	(0.661)
Num. Climate Patents F.E.	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	13130	11023	9080	12890	10889	8974
adj. R^2	0.945	0.946	0.948	0.803	0.798	0.795

Table A8. Supplier's Climate Innovation and CO2 Emissions for Customers of Customers

This table presents an extention of Table 5 and studies the emissions by customers of customers. Each observation represents a supplier × customer × year, indicating that the supplier sells goods or services to the customer in that specific year. It is not necessary for the supplier-to-customer sale to be non-missing. The dependent variable is the customer's customer future Scope 1 (Scope 2 in Panel B) CO2 emissions in year $t+k$, where $k = 1, 2$, and 3. The variable "*Supplier's Climate Patent Ratio [t]*" represents the ratio of newly invented climate patents in year t by the supplier in the given supplier-customer pair. The variable "Supplier's General Patent Number [t]" denotes the total number of newly invented general patents in year t by the supplier. Fixed effects for supplier × customer pairs are consistently included. Standard errors are clustered at the customer-firm level. Statistical significance is denoted by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. To enhance readability, all coefficients are multiplied by 100.

Panel A: Supplier-Customer Pair Sample (Scope 1 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer of Customer	Scope 1 Emission Total			Scope 1 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Supplier's Climate Patent Ratio [t]	-1.449***	-1.536**	-1.814**	-1.177**	-1.550**	-1.625**
	(0.515)	(0.674)	(0.860)	(0.494)	(0.638)	(0.787)
Supplier's General Patent Number [t]	2.091***	2.413**	1.315	1.969***	1.046	-0.239
	(0.810)	(1.083)	(1.350)	(0.761)	(0.983)	(1.210)
Customer Firm Controls	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	265263	119905	72485	260858	117584	70932
Adj. R^2	0.978	0.981	0.981	0.969	0.975	0.977

Panel B: Supplier-Customer Pair Sample (Scope 2 Emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer of Customer	Scope 2 Emission Total			Scope 2 Emission Intensity		
Measured in	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
Supplier's Climate Patent Ratio [t]	-0.972*	-0.802	-1.885*	-0.679	-0.688	-1.519
	(0.525)	(0.830)	(1.074)	(0.493)	(0.782)	(1.007)
Supplier's General Patent Number [t]	-0.052	1.328	2.169	-0.242	-0.054	0.646
	(0.763)	(1.215)	(1.483)	(0.695)	(1.123)	(1.353)
Customer Firm Controls	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y
Supplier-Customer Pair F.E.	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y
Num. Obs.	265496	120069	72618	261091	117748	71065
Adj. R^2	0.952	0.942	0.937	0.844	0.830	0.824

Table A9. Climate Patent Ratio and New Customer Firms (Extensions)

This table presents extensions of Table 10. In Panel A, climate patents are split based on their market value. Every year, we sort all climate patents into two groups according to the market value of patents measured in Kogan et al. (2017). Climate Patent Ratio (High Value) is defined as the number of high-value climate patents divided by all new patents invented by the given firm in year $t-1$. In Panel B, climate patents are split based on the relatedness between each climate patent and its holder's product descriptions. The relatedness is calculated following the procedures in Figure 1. Panel C interacts the climate patent ratio in year $t-1$ with the MCCC index as constructed in Ardia et al. (2022). Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A: Patents Split by KPSS Patent Value

	(1)	(2)	(3)	(4)
	Number of New Customer Firms			
Customer Split by	Environmental Score		Total GHG Emissions	
	High	Low	High	Low
Supplier's ⋯				
Climate Patent Ratio (High Value) × Post 2010	0.134***	0.074	0.167***	-0.014
	(0.051)	(0.054)	(0.064)	(0.050)
Climate Patent Ratio (Low Value) × Post 2010	0.024	-0.105***	-0.048	-0.057
	(0.053)	(0.037)	(0.053)	(0.053)
Firm Controls	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y
Num. Obs.	30285	30285	27811	27811
Adjusted R^2	0.203	0.234	0.273	0.342

Panel B: Patents Split by Product-to-Patent Relatedness

	(1)	(2)	(3)	(4)
	Number of New Customer Firms			
Customer Split by	Environmental Score		Total GHG Emissions	
	High	Low	High	Low
Supplier's ⋯				
Climate Patent Ratio (High Related) × Post 2010	0.139**	-0.005	0.155**	-0.048
	(0.066)	(0.053)	(0.074)	(0.059)
Climate Patent Ratio (Low Related) × Post 2010	0.073	0.010	0.048	-0.097*
	(0.056)	(0.051)	(0.072)	(0.050)
Firm Controls	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y
Num. Obs.	30285	30285	27811	27811
Adjusted R^2	0.203	0.234	0.273	0.342

Panel C: Interaction with MCCC Index

	(1)	(2)	(3)	(4)
	Number of New Customer Firms			
Customer Split by	Environmental Score		Total GHG Emissions	
	High	Low	High	Low
Supplier's ⋯				
Climate Patent Ratio	-0.070	-0.061	-0.177***	-0.055
	(0.044)	(0.043)	(0.046)	(0.048)
Climate Patent Ratio × MCCC Index	0.006**	0.006**	0.013***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Firm Controls	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y
Num. Obs.	23062	23062	22598	22598
Adjusted R^2	0.192	0.222	0.248	0.325

Table A10. Climate Patent Ratio and New Customer Firms (Considering Switching Cost)

This table investigates the relationship between the number of newly acquired customer firms and a supplier's climate patenting activity, with a particular focus on how switching costs may influence this association. The regression sample includes all CRSP-Compustat firms that form at least one new supplier–customer relationship between 2005 and 2021, excluding firms in the financial, retail, and wholesale sectors. The dependent variable is the number of new customer firms establishing a relationship with supplier firm i in year t. The key explanatory variable, $Climate; Patent; Ratio_{t-1}$, is defined as the ratio of newly granted climate-related patents (Y02 classification) to total patents for firm i in year $t-1$. To account for time variation, we include indicator variables for the post-2010 and pre-2010 periods. We also control for the firm's total number of newly granted patents in year $t-1$. Columns (1) to (3) partition new customer firms based on firm size, as measured by total book assets. Columns (4) to (6) categorize new customer firms based on the product similarity between their existing suppliers and the focal supplier, capturing the role of switching frictions in shaping supplier choice. Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Industry (NAICS 4-digit) fixed effects are included in columns (1) to (3), and firm F.E. are added in columns (4) to (6). Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Dependent Variable = Number of New Customer Acquisition							
Count New Customers with	Customer Firm Size				Customer's Other Supplier's Product Similarity			
	High	Low	High	Low	High	Low	High	Low
Climate Patent Ratio [t-1] × I[Post 2010]	0.103***	-0.039	0.074**	-0.020	0.033	0.007	0.073**	-0.008
	(0.030)	(0.026)	(0.034)	(0.031)	(0.025)	(0.025)	(0.030)	(0.031)
Climate Patent Ratio [t-1] × I[Before 2010]	-0.035	0.002	-0.044	0.026	-0.022	-0.027	0.020	-0.052
	(0.023)	(0.024)	(0.035)	(0.033)	(0.043)	(0.044)	(0.047)	(0.049)
Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Industry F.E.	Y	Y			Y	Y		
Firm F.E.			Y	Y			Y	Y
N	28364	28364	28194	28194	29566	29566	29394	29394
adj. R^2	0.123	0.150	0.178	0.219	0.166	0.150	0.242	0.211

Table A11. First Stage Regression when using State R&D Tax Credits as Instrument

This table reports the first stage regression for Table 6 using the regular firm × year sample instead of the stable supply chain pair sample. The setup remains identical to that of Table 6 (see there for details and variables). Standard errors are clustered at the firm level. Statistical significance is indicated by *, **, and ***, corresponding to significance levels of 10%, 5%, and 1%, respectively. For ease of interpretation, all coefficients are multiplied by 100.

	(1)	(2)	(3)	(4)	(5)	(6)
First Stage	Number of Climate Patents by Suppliers			Number of General Patents by Suppliers		
State R&D Tax Credits [t-1]	2.289***			2.557***		
	(0.817)			(0.718)		
State R&D Tax Credits [t-2]		2.061***			1.902***	
		(0.709)			(0.610)	
State R&D Tax Credits [t-3]			2.253***			1.479***
			(0.676)			(0.563)
Firm F.E.	Y	Y	Y	Y	Y	Y
Calendar Year F.E.	Y	Y	Y	Y	Y	Y
N	102629	102629	102629	102629	102629	102629
adj. R^2	0.699	0.699	0.699	0.772	0.772	0.772

Table A12. Tests for the Exogeneity of Supplier Choice in the M&A Difference-in-Differences Setup

The regression sample includes 1,778 supply chain relationships in which the supplier is successfully acquired by another firm. It analyzes whether the customer's choice to continue with the old supplier after it is acquired (i.e., its choice to adopt the old supplier's acquirer as a substitute supplier) is associated with the acquirer's climate innovativeness (Climate Patent Ratio) or with the customer's incentive to decarbonize (proxied by its Scope 1 emissions and its change in Scope 1 emissions). The dependent variable is a dummy equal to one if the customer firm adopts the acquirer as a substitute supplier after the original supplier is acquired, and zero if the customer either chooses a different supplier or does not add any new supplier following the merger. The variables *Climate Patent Ratio* and *Number of Climate Patents* are measured for the acquirer during the three years preceding the year when the merger became effective. *Scope 1 Emissions* measure the customer's emissions in the year of the merger.

	(1)	(2)	(3)	(4)
Dependent Var. =	**I[Retain Acquirer as New Supplier]**			
Climate Patent Ratio (Acquirer)	0.128 (0.155)			
Num Climate Patents (Acquirer)		0.005 (0.011)	0.106 (0.062)	0.011 (0.017)
Scope 1 Emissions (Customer)			0.032 (0.020)	
Num Climate Patents (Acquirer) × Scope 1 Emissions (Customer)			-0.008 (0.006)	
Δ Scope 1 Emissions (Customer)				-0.018 (0.021)
Num Climate Patents (Acquirer) × Δ Scope 1 Emissions (Customer)				0.022 (0.023)
Year F.E.	Y	Y	Y	Y
N	1778	1778	727	685
R^2	0.047	0.047	0.045	0.045

A The Examiner Leniency Instrument for Determinants of New Customer Acquisitions

We describe in this Appendix our identification strategy for the tranmission channels of the acquisition of new customers, as investigated in Table 10. Our identification strategy leverages quasi-random shocks in the probability of patent approvals. Specifically, we use patent examiner leniency as an instrumental variable for the number of climate patents issued to a supplier firm. Indeed, the literature has shown that some patent examiners are more lenient and grant patents more easily than others in the same field, often due to person-specific, idiosyncratic reasons (Cockburn et al., 2002). Moreover, in most USPTO technology art units, patent examiners are assigned to applications in a quasi-random fashion (Sampat and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2020). Since examiners are randomly assigned, the leniency shock is likely to be orthogonal to any remaining confounding effects (omitted variables) that are correlated with the number of newly acquired customer firms.[49]

We posit that the granting of climate patents has a significant signaling effect in attracting new customers.[50]

We separate each firm's patent applications into climate-related and non-climate-related applications. We use the difference in leniency attitudes between examiners reviewing climate-related and non-climate-related patent applications to instrument for the key independent variable, the climate patent ratio. We hypothesize that when a firm is fortunate in being assessed by lenient examiners for their climate patent application but faces relatively stricter scrutiny for their non-climate patent application, it leads to an exogenous positive shock to the firm's climate patent ratio. The Examiner Leniency Difference is defined as,

$$\begin{aligned}\text{Examiner's Leniency Difference}_{i,t} = \frac{1}{N_{clim}} \sum_{p \in \text{Clim}}^{N_{clim}} [\text{Examiner Leniency}_{p,e}] - \\ \frac{1}{N_{non\text{-}clim}} \sum_{p \in \text{Non-Clim}}^{N_{non\text{-}clim}} [\text{Examiner Leniency}_{p,e}], \quad (12)\end{aligned}$$

where N_{clim} ($N_{non\text{-}clim}$) is the number of climate (non-climate) patent applications submitted by firm i and receive decisions (granting or rejection) from the USPTO in year t. Examiner $\text{Leniency}_{p,e}$ is the leniency of the examiner e who reviews the given patent application p. Specifically, it is constructed as

$$\text{Examiner Leniency}_{p,e} = \frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1} - \frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1} \quad (13)$$

$\frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1}$ is examiner e's all-time granting ratio in her career in the USPTO, excluding

[49] This identification strategy is not suitable for the analysis of carbon emission effects. As we discuss below, the patent status of a new climate technology alone should not influence its role in customer decarbonization.

[50] Since 2001, the USPTO has been required to publish most patent application documents 18 months after their filing date. However, we argue that most managers of customer firms are not technology specialists and generally do not consistently check the publication database in the USPTO patent publication system. Therefore, in this section, we use the patent grant date to construct our primary explanatory variable, the climate patent ratio. We thank Alminas Zaldokas for bringing this issue to our attention.

the focal application p (the standard leave-one-out method in Melero, Palomeras, and Wehrheim (2020)). When calculating an examiner's leniency, we use all patent applications, including climate and non-climate patent applications. We require each examiner to examine at least ten applications in the dataset. The same method applies to calculating the average granting ratio of the art unit to which the application is assigned and to which examiner e belongs: $\frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1}$. Hence, our leniency measure is a relative leniency measure within an art unit. Table A2 offers summary statistics of this IV sample.[51]

Columns (1) and (2) in Table 11 depict the first-stage regressions for our instrumental variable. Notably, the Instrumental Variable (IV) —— Examiner's Leniency Difference —— exhibits a strong and positive predictive relationship with the climate patent ratio. To illustrate intuitively, if a firm happens to encounter more lenient examiners on average for its climate patent applications compared to its non-climate applications, it tends to possess a higher climate patent granting ratio. Moreover, the robustness of our first-stage results persists even after accounting for the climate patent application ratio (defined as the ratio of climate patent applications to non-climate patent applications) in column (2). The strong F-tests indicate that it is unlikely that our approach is affected by a weak instrumental variables problem.

The second-stage regressions are presented in the remaining columns of Panel A. Consistent with our prior analyses, we consistently incorporate interaction terms between the climate patent ratio and dummies for the periods before and after 2010. Consequently, when instrumenting the climate patent ratio, we instrument these two interaction terms as well. The robustness of the first-stage regressions for these interaction terms remains strong and successfully clears the weak instrument test.

For each year, we conduct a sample split among all new customer firms based on the annual median environmental score. Subsequently, we define two new dependent variables: the count of new customers with high and low environmental scores, detailed in Panels A (columns (6) – (8)).[52] Similarly, Panel B deploys a sample split using total GHG emissions (Scope 1+2). In Table 11, we find exactly the same results as in Table 10: (i) Supplier's climate innovation becomes a catalyst for attracting new customers post-2010; (ii) this effect is magnified for new customers with high environmental scores and elevated emissions. These outcomes should alleviate concerns regarding omitted variable bias and bolster the case for a causal interpretation.

The examiner leniency instrument aims at studying an exogenous shock in the capacity to attract *new* customers. It relies on random variations in patent grants, with the identifying assumption that the patent award itself matters, not in the underlying technology: climate patents serve as a "certification" for new customers and prevent industry competitors from developing similar technology, but presumably are less important for existing customer relationships. Since the tests in Table 10 focus on the acquisition of new customers where the prestige and visibility of a USPTO grant likely matters, this is a reasonable assumption (by contrast, in existing supply chain relationships with their often dense communication channels, the technology rather than the patent status should play a greater role). This distinction implies that the leniency instrument will likely not be effective for customers' CO2 emissions (see Table 3). Indeed, as expected, we find (in unreported regressions) that the examiner leniency shock has no impact on emissions of existing customers.

[51] Hege, Pouget, and Zhang (2024) use the same IV. We follow the details of their construction.

[52] We use the ln(1+x) transformation for our dependent variables because Poisson regressions in the first stage are called forbidden regressions and are theoretically wrong in econometrics.

B Variable Definitions and Construction

Variable Name	Definition of Variable	Data Source
Customer Firm × Year Sample – Table 3, 4, 7		
GHG Emissions (Scope 1) – Total	natural logarithm of greenhouse gas emissions in tons (Scope 1) emitted by firm i in year t	S&P Trucost
GHG Emissions (Scope 1) – Intensity	natural logarithm of greenhouse gas emission intensity (total emissions scaled by sales) (Scope 1) emitted by firm i in year t. Sales are adjusted by 2000 CPI in the US.	S&P Trucost
GHG Emissions (Scope 2) – Total	natural logarithm of greenhouse gas emissions in tons (Scope 2) emitted by firm i in year t	S&P Trucost
GHG Emissions (Scope 2) – Intensity	natural logarithm of greenhouse gas emission intensity (total emissions scaled by sales) (Scope 2) emitted by firm i in year t. Sales are adjusted by 2000 CPI in the US.	S&P Trucost
Supplier's Climate Patent Ratio	weighted climate patent ratio of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate patents newly filed divided by the total number of patents filed in year t	PatentsView
Supplier's Number of General Patents	weighted number of general patents of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The number of general patents is the total number of patents (ultimately granted) filed by a firm in year t, and we use the $\ln(1+x)$ transformation.	PatentsView
Customer's Climate Patent Ratio	climate patent ratio of the customer firm in the observation	PatentsView
Supplier's Climate Patent Ratio (Process Patents)	weighted climate patent ratio (only process patents) of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate process patents (ultimately granted) newly filed divided by the total number of process patents filed in year t	PatentsView
Supplier's Climate Patent Ratio (Product Patents)	weighted climate patent ratio (only product patents) of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate product patents (ultimately granted) newly filed divided by the total number of product patents filed in year t	PatentsView
I[New Supplier with Climate Patents]	dummy variable equal to 1 if the firm obtains a new supplier with a climate patent ratio greater than 0.2. The climate patent ratio is calculated using the supplier's patent information from years $t-2$, $t-1$, and t	PatentsView

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Appendix B continued from previous page

Variable name	Definition of variable	Data Source
I[Old Supplier with Climate Patents]	dummy variable equal to 1 if the firm has long-standing suppliers (relationships starting 5 years ago) with a climate patent ratio (in years $t-2$, $t-1$, and t) greater than 0.2	PatentsView
Firm Size (MarketCap)	firm size, measured as natural logarithm of the firm's market capitalization (Compustat item $CSHO_t$ × item $PRCC\_F_t$)	CRSP-Compustat
Tobin's Q	Market-to-book ratio in assets. Market value of assets equals the book value of assets (item AT_t) + the market value of common equity at fiscal year-end (item $CSHO_t$ × item $PRCC\_F_t$) − the book value of common equity (item CEQ_t) − balance sheet deferred taxes (item $TXDB_t$)	CRSP-Compustat
R&D	R&D expenditure, measured as item XRD_t scaled by lagged book assets (item AT_{t-1}). If this variable is missing, we replace it with the industry-year median R&D expenditure.	CRSP-Compustat
Cash	defined as cash and cash equivalents (item CHE_t) scaled by lagged book assets	CRSP-Compustat
ROA	return on assets, defined as EBITDA scaled by lagged book assets	CRSP-Compustat
Book Leverage	book leverage, defined as debt including long-term debt (item $DLTT_t$) plus debt in current liabilities (item DLC_t) divided by the sum of debt and book value of common equity (item CEQ_t)	CRSP-Compustat
CAPX	capital expenditure, measured as item $CAPX_t$ scaled by lagged book assets	CRSP-Compustat
PPE	natural logarithm of firm's value of plants, properties, and equipment (PPE)	CRSP-Compustat
Discrete Choice Model Sample – Table 9		
I(Supplier-Customer Match) [Dependent Variable]	dummy variable equal to 1 if the customer firm c selects the supplier firm s to purchase goods or services in year t	FactSet
Supplier's Climate Patent Ratio [t-1]	supplier's climate patent ratio in year $t-1$. Climate patent ratio is the ratio of climate patents among all patents filed by the supplier. We calculate patents here using patent application year	PatentsView
Supplier's Num General Patents	number of general patents filed by a supplier	PatentsView
I(Post 2010)	dummy equal to 1 after 2010 (not including 2010)	
I(Before 2010)	dummy equal to 1 before 2010 (including 2010)	
Customer's Environmental Score	customer firm's environmental score	MSCI and Refinitiv
Customer's Social Score	customer firm's Social score	MSCI and Refinitiv
Customer's Governance Score	customer firm's Governance score	MSCI and Refinitiv

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Appendix B continued from previous page

Variable name	Definition of variable	Data Source
Supplier × Year Sample – Figure 4 and Table 10, 12, 11		
Number of New Customer Firms	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before	FactSet
Number of New Customer Firms (with High E-Score)	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before. For each year, we sort all new customer firms into two groups by median. Customer firms with high E-score are firms with above median environmental ratings.	FactSet
Number of New Customer Firms (with High Emissions)	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before. For each year, we sort all new customer firms into two groups by median. Customer firms with high emissions are firms with above median emission intensity.	FactSet

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