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

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Abstract

We study the effect of climate-related innovation on carbon emissions by analyzing supply chain networks. We find that climate innovation reduces carbon emissions at customer firms, driven by product innovations. The effect is economically significant, dominated by the most emission-intensive customer firms, gradually increases over a five-year horizon, and is significant for Scope 1 and Scope 2 emissions. We analyze transmission mechanisms by exploring customers' choice of suppliers in reaction to climate patent announcements and show that customers exhibit a strong preference for suppliers with climate innovations. We find that climate patents also allow suppliers to attract new customers, especially customers with high environmental ratings or a large carbon footprint. Using the quasi-random assignment of patent examiners and the exogenous technological obsolescence of climate patents as instruments suggests a causal interpretation of the main findings.

Key words: climate innovation; supply chains; new customer firms; carbon emissions; ESG scores; discrete choice models.
JEL classification: O33, Q54, Q55.

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1 Introduction

It is widely assumed that climate innovation will have to play a central role in the global transition to climate neutrality. In its influential transition scenarios to net zero by 2050, the International Energy Agency reckons that half of the reductions in 2050 will come from new technologies that today exist only as prototypes and are not used at scale (IEA, 2021). According to the recent 6th Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), climate innovation will have to play a major role in pursuit of the Paris Agreement goals of 2015 (IPCC, 2022).

A lot is at stake for climate innovation and there is also a large production of climate patents: the US patent 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.[1] But is there evidence that climate innovation actually has a meaningful and measurable impact on greenhouse gas (GHG) emissions? There is scant micro-level research on this question. Bolton, Kacperczyk, and Wiedemann (2023), the only firm-level analysis, provide sobering evidence by documenting that climate-related patents have no significant impact on the innovators' carbon emissions, neither for renewable or clean energy technologies (green patents) nor for improvements in fossil energy efficiency (brown patents), and regardless of the horizon considered. Bolton et al. (2023) attribute this finding to a rebound effect, the idea that fossil energy savings may simply induce a larger demand for energy (also known as the Jevons paradox, following Jevons (1865)). However, their study has important limitations. Most importantly, they focus on carbon emissions of innovating firms and possible technology spillovers to peer firms where they also find no effect.

Many climate patents, however, are product innovations and hence the emission benefits should accrue at the customers that use the innovator's products.[2] Looking at the innovating firm then misses the place where emission savings are expected to occur. This is a relevant concern: we show in our study that more than 70% of US climate innovation are product innovations, and hence their principal emission impact should not be observable when studying innovators and their peers.

[1] Starting in 2010 and following an appeal of the UNFCCC (United Nations Framework Convention on Climate Change), USPTO and EPO (European Patent Office) have launched and progressively expanded the joint Y02/Y04S tagging scheme to identify climate-related patents, and later applied to scheme backwards to patents before 2010. The number of patents classified by the USPTO under this scheme as climate-related has strongly increased until 2015 and since then maintained a fairly stable level (EPO, 2015; Angelucci, Hurtado-Albir, and Volpe, 2018). Our paper is based on the Y02/Y04S tagging scheme.

[2] For example, if an aircraft or jet engine manufacturer patents technology for fuel-saving aircraft models, the emission savings should occur at the airline customers, not at the aircraft or engine manufacturer.

In this paper, therefore, we study the emission impact of climate patents by looking at the emissions of the innovator's customers. We are also interested in understanding the technology and knowledge diffusion of climate technology in supply chain networks, looking at intensive and extensvie margin. We ask: what type of customer firms will generate the largest emission reduction when adopting climate-related product innovation? And do product-related climate patents help innovators to acquire new business customers, and what types of new customers will choose climate innovators as their new suppliers?

To analyze the emission impact in existing supply chain networks, we identify important customers using the FactSet Revere supply chain database, widely used in research on supply chains. We identify product innovations following Bena, Ortiz-Molina, and Simintzi (2022) and find that almost 70% of climate patents are product innovations. We then construct a supplier-firm $\times$ customer-firm $\times$ year sample by merging the data from FactSet Revere 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 CO2 emissions of customers. We find this effect consistently for Scope 1 (direct) and Scope 2 (indirect) emissions, and for total emissions (in tons of CO2) as well as for emissions intensities (total emissions divided by firm output),[3] 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. To the best of our knowledge, we are the first to provide firm-level evidence that climate patents generate actual GHG emission reductions.

Importantly, we confirm this finding in a panel of stable supplier-customer pairs with supplier-customer pair fixed effects. This serves as an initial step to address concerns about selection effects, concerns that firms aiming to reduce emissions might be more prone to opt for climate innovators as suppliers, potentially without a direct causal link between supplier climate patents and customer emissions. Furthermore, we use the exogenous technology obsolescence (Ma, 2022) of climate patents as an instrument to shock the climate innovation capacity of supplier firms to sharpen the causal interpretation of our findings. The results confirm our findings and provide additional support for our interpretation that the emission effect is causal. When we apply the same analysis to climate patents granted foro process innovations, we find much weaker effects, indicating that the impact on customers is predominantly

[3] The distinction between total emissions and emissions intensity is important as they often deliver inconsistent results and in light of concerns about rebound effects (Bolton and Kacperczyk, 2021a, 2022; Lioui and Misra, 2023).

realized when climate innovation is embedded in products.

We find that the impact is stronger for high-emission customers and in the most emission-sensitive technology categories (energy, transportation, buildings); it is weaker and less stable in other technology categories such as information and communication technologies but remains significant. It is also more pronounced when the innovator's main sector belongs to resource extraction (in particular coal mining), manufacturing, or transportation.

In theory, it should be possible to measure customer emissions via the innovator's Scope 3 emissions that contain all indirect emissions (not included in Scope 2) that occur in the (upstream and downstream) value chain of the supplier. However, when we extend the analysis and look at innovators' downstream Scope 3 emissions, we find no significant effect of climate patents related to product innovations, echoing similar evidence of Bolton et al. (2023) on downstream Scope 3 emissions. We discuss possible reasons why Scope 3 measures might miss the emission effects in supply chain networks that we document, including the heavy biases in Scope 3 emission data (Klaaßen and Stoll, 2021).

Turning to our questions on the dynamics of knowledge diffusion at the extensive margin, we investigate whether climate innovations help suppliers to expand their business and attract new customers. This is a crucial question to understand whether climate technology is indeed widely adopted (Hall and Helmers, 2010), as assumed e.g. in the IEA (2021) scenarios. "Business stealing" is generally an important question in the innovation literature (Cohen, 2010) and it should be highly relevant when studying the dynamics of supply chain relationships (Pankratz and Schiller, 2021). But curiously, the effect of innovation in attracting new customers has not formally been studied in the supply chain literature so far. It is not obvious that climate innovation will facilitate the acquisition of new customers or "business stealing": reducing GHG emissions is costly and may eat into profit margins, and climate innovators are also likely to charge a premium for climate-friendly products. On the other hand, growing attention to carbon footprints and corporate climate action creates incentives to reduce emissions nonetheless.[4]

To test this hypothesis, we first try to understand the customer's preferences for suppliers featuring climate innovation. We construct an empirical discrete choice model (McFadden, 1974) regarding the selection of potential suppliers by customer firms.[5] For each customer firm that has at least one supplier

[4]There are two major arguments in support of this idea. First, as climate change garners more attention, there is an increased demand and consumer willingness-to-pay for greener products. Second, the growing interest in sustainable investments means that financial markets increasingly incorporate climate risks into security prices, resulting in a lower cost of capital for firms with lower transition risk.

[5]Strictly speaking, the establishment of supplier-customer relationships is a two-sided matching process. How-

in a given year, we create a set of alternatives (potential suppliers) that consists of two categories. The first category includes suppliers that are selected by the customer firm. The second category includes suppliers that produce similar products to the selected suppliers but are not chosen by the customer. We construct the second set of (potential) suppliers using Hoberg and Phillips (2016)'s text-based product descriptions and network industry classification (TNIC). Our regression analysis shows strong evidence that 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 that supplier. Moreover, we observe that this preference is even stronger for customer firms with higher environmental scores or higher initial carbon emissions. To further validate our findings, we conduct an alternative specification where we focus solely on the choices of new suppliers. This analysis strengthens the case that customers actively make choices and that the observed effect is not solely explained by continued supply chain relationships.

Next, we examine the suppliers' capacity for business expansion. Our regression analysis reveals that suppliers' climate innovation does attract new business customers. Specifically, an increase in the interquartile range of the climate patent ratio of a supplier is associated with a 7.35% – 22.06% increase in the number of new business customers obtained by the supplier between 2011 and 2021. Interestingly, these coefficients are not significantly different from zero between 2005 and 2010. While we are not able to pinpoint a specific cause for the absence of significant effects prior to 2010, we note that a heightened public attention to climate change following the failure of the COP15 meeting in Copenhagen 2009[6] and other concurrent developments has been documented in the literature (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022), as well as a structural break around 2010 in the valuation gap between high-emission and low-emission firms (Choi, Gao, Jiang, and Zhang, 2022). The creation of the "Y02/Y04S" patent tagging scheme in 2010 may also have raised attention for the importance of climate-related patents(EPO, 2015). Consistent with the notion of a structural break in 2010, we conduct event studies following Kogan, Papanikolaou, Seru, and Stoffman (2017) that confirm a positive jump in the value of climate patents after 2010, with no comparable effect in the value of general patents around this time.

Investigating transmission channels for the capacity to attract new customers, we find that new

ever, it is often observed that customer firms have significantly greater bargaining power during the selection process. Schiller (2018) documents that, on average, customer firms are ten times larger in terms of book value of assets and five times larger in terms of market capitalization compared to the average supplier.

[6]The unexpected failure of COP15 to produce a new global climate agreement which was widely perceived as a shock. An agreement was finally concluded six years later at COP21 in Paris.

customer firms with high environmental scores or with high GHG emissions are more likely to switch to suppliers offering products that embed climate innovation. A high environmental rating is considered to be a proxy for a firm's environmental and climate mitigation preferences, i.e. firms with high environmental ratings should have a higher willingness-to-pay for climate-innovative products.[7]

Finally, we delve into the types of climate patents that have the most significant impact on the acquisition of new customers. Our findings reveal that climate patents with higher market value, measured following Kogan et al. (2017), and those that exhibit a strong relationship with the supplier's core products play a more crucial role in attracting new customers. It is worth noting that the innovation literature lacks a measure that effectively links patents to the products of innovators (Argente, Baslandze, Hanley, and Moreira, 2020). To address this gap, we develop a novel text-based measure. Following the methodology used in Kogan, Papanikolaou, Schmidt, and Seegmiller (2021), our method uses natural language processing, specifically the Stanford GloVe model, to compute the pairwise document 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. A higher cosine similarity score indicates a stronger connection between the patent and the company's core products. In our regression analysis, we observe that climate patents with higher cosine similarity score have a more pronounced impact on the acquisition of new customers.

We revisit the concern that our analysis might be affected by endogeneity problems, in particular the concern that selection effects masked by omitted variables attract new corporate customers and are correlated with climate innovation, such as the possibility that other green or ESG-related firm policies, rather than climate patents. We introduce two instrumental variables to address such omitted variable concerns. Our first identification strategy exploits exogenous shocks in the probability of patent approvals arising from the quasi-random assignment of lenient or tough patent examiners in most USPTO technology art units (Sampat and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2020; Cockburn, Kortum, and Stern, 2002).[8] We use the patent examiner leniency as an instrumental variable (IV),

[7] In the growing theory literature explaining non-monetary corporate ESG preferences, e.g. Bénabou and Tirole (2010) argue that firms' CSR behavior could be explained by their internal belief in "doing well by doing good" (Baron, 2001) or by the personal preferences of the firm's CEO or board members. The revealed preference of high-emission customer firms could be explained, first, by the presence of climate-conscious institutional investors pushing for a reduced carbon footprints (Atta-Darkua, Glossner, Krueger, and Matos, 2022) and, second, the fact that high carbon emissions are associated with higher costs of capital (Bolton and Kacperczyk, 2021b).

[8] Patent applications are assigned to art units of patent examiners by technological specialization. There are about 900 art units, so they are a fairly granular subdivision of the patent examination process.

following the literature that the leniency shock is likely orthogonal to any remaining firm-level omitted variable bias. Our second instrument is technology obsolescence following Ma (2022), based on the rationale that more obsolete knowledge is less likely to be at the frontier of climate technology and that the aging of an innovator's knowledge base is determined by technology shocks of other innovators, and hence exogenous for the innovator under consideration. Using these two instrumental variables in 2SLS regressions, we corroborate our two main findings.

Literature: Our paper contributes to three strands of the literature. First, our paper contributes to the growing literature regarding climate and green innovation and its effects and determinants in finance and economics. Dechezleprêtre, Glachant, Haščič, Johnstone, and Ménière (2011) use PATSTAT data to examine the dynamics, distribution, and international transfer of patented inventions in 13 climate change mitigation technologies between 1978 and 2005. Furthermore, Aghion, Dechezleprêtre, Hémous, Martin, and Van Reenen (2016) construct new firm-level panel data on auto industry innovation distinguishing between "dirty" (internal combustion engine) and "clean" (e.g., electric, hybrid, and hydrogen) patents across 80 countries. 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 listed firms in the energy sector contribute a lot to green patents but receive lower ESG ratings and are frequently excluded from investing scopes of ESG funds. Extending the analysis to non-listed firms, Dalla Fontana and Nanda (2022) show that climate patents granted to firms backed by venture capitalists represent a small share of climate patents but that these patents are more likely to cite fundamental science and to be subsequently cited. Bolton et al. (2023) document that climate innovation is path-dependent and has no significant impact on the innovators' future carbon emission reductions. Reza and Wu (2022) show evidence that government-led environmental regulation influences corporate innovation policies. Kuang and Liang (2022) show that while firms with high carbon risk firms and low activity in climate patenting show significant underperformance in risk-adjusted long-run stock returns, there is no underperformance for peers with similar high carbon risk but high levels of climate innovation. Looking at green patents in general (not necessarily related to climate), Reza and Wu (2022) show that environmental regulation and firms' exposure to regulatory risk positively affect the value of green innovation. There is some controversy, however, as Andriosopoulos, Czarnowski, and Marshall (2022) compare green patents with other patents through event studies and find no evidence that investors value green innovation.

Second, our paper is closely related to recent work on climate finance and the supply chain. Schiller (2018) and Dai, Liang, and Ng (2021b) both show that ESG policies of customer firms can propagate to supplier firms, but not vice versa. Similarly, HomRoy and Rauf (2023) show that supply chain connections influence the adoption of climate-responsible policies. Furthermore, Pankratz and Schiller (2021) find that customer firms are more likely to terminate the existing supplier-customer relationships if the 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. Lastly, Dai, Duan, Liang, and Ng (2021a) provide empirical evidence that firms outsource part of their carbon emissions to foreign suppliers. To the best of our knowledge, we are the first to exploit the real impact of climate-related technologies on the supply chain.

Third, our paper is related to a small literature on corporate innovation in the supply chain. Delgado and Mills (2020) show that firms in supply chain industries tend to be more innovative than firms in business-to-consumer industries. Isaksson, Simeth, and Seifert (2016) show that buyer innovation in supply chain networks leads to an increase in supplier innovation. Chu, Tian, and Wang (2019) find that customer geographic proximity increases supplier innovation. In contrast, Todo, Matous, and Inoue (2016) find that distant Japanese suppliers that embody more diversified knowledge improve productivity more than neighboring suppliers. Looking at industry linkages, Dong, Liu, Tang, and Qiu (2023) find for Chinese listed firms that the innovativeness of upstream industries positively impacts customer innovation. We contribute to this literature the analysis of the acquisition of new customer firms following supplier innovation that to our knowledge has not been investigated so far. There is also a small literature focusing on green innovation in the supply chain. Chen, Wang, and Zhou (2019) show theoretically that supplier and customer firms can increase profits and environmental benefits when they cooperate on their R&D strategies. Looking at industry-level evidence, Costantini, Crespi, Marin, and Paglialunga (2017) find evidence that innovative activities have an impact on the sectoral environmental performance in the innovating sector as well as the downstream purchasing sectors. We contribute to this literature the analysis of firm-level evidence on the impact of supplier innovation on customer GHG emissions.

The paper is organized as follows. We explain our data strategy and main variables and provide summary statistics in Section 2. In Section 3, we present the first part of our main analysis, dedicated to the link between supplier climate patents and GHG emissions at customer firms. The second main part, knowledge diffusion of climate patents by their capacity to win new customers, is presented in Section

4. In Section 5, we address endogeneity concerns and present two distinct identification strategies that confirm our main results. 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 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]

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

[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. When sorting patents by year of filing, 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.

[11]We exclude patents with the Y02A and Y04S tags, patent tags that are narrowly dedicated to innovations in climate adaptation and smart grids respectively as there are very few patents tagged as Y02A or Y04S.

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

process patent if its first claim (usually the most important claim) begins with the words "a process of," "a method of," "a method for," and so on. About 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.

For our extensions and for the instrumental variables (IV) approach used in Section 5, we also use patent application data and information about USPTO examiners obtained from the USPTO Patent Examination Research dataset.[13] The forward and backward citation data are from PatentsView.org.

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 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.[14] When we require that a given customer has non-missing ESG ratings in any 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

[13]For details about this dataset, see Graham, Marco, and Miller (2018).
[14]The FactSet Revere begins its supply-chain data in 2003.

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 observation 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 the manufacturing industry (33) and customers in the manufacturing industry (33), accounting for 12.47%. The second largest group is the information-to-information supplier-customer relationship.

2.3 ESG and CO2 Emission Data

To investigate which subset of business customers are attracted by suppliers' climate innovation, we obtain environmental ratings for customer firms from three ESG-rating data providers: (i) LSEG ESG (formerly Refinitiv ESG, and originally Asset4), (ii) Sustainalytics, and (iii) S&P Global ESG rating. Following Brandon, Glossner, Krueger, Matos, and Steffen (2020), we create a composite environmental score based on the three distinct environmental evaluations in order to maximize the sample coverage,

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

Specifically, we first transform those raw environmental scores into three standard z-scores with a mean equal to zero and a standard deviation equal to 1. Next, we take the equal-weighted average for k z-scores conditional on the fact that there are k non-missing environmental scores for that firm. $1_{A4,it}$ is an indicator variable equal to 1 if firm i is covered in LSEG ESG in year t.

Furthermore, we obtain firm-level CO2 emission data from S&P Trucost. Trucost provides CO2 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 the Scope 1 and Scope 2 in our main analysis since there is evidence of a strong bias in Scope 3 emission data that we discuss below.[15]

[15]Scope 3 emissions contain all indirect emissions (not included in Scope 2) that occur in the value chain of the

2.4 Summary Statistics

In our analysis of customer emissions in Section 3, we focus on a customer firm × year sample, which requires that each customer firm has at least one CRSP-Compustat supplier offering products or services to it in the 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 company 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 company 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 supplier climate patent ratio is 1.6%, suggesting that most suppliers make little effort in climate innovation. In the subsample in which we require that suppliers file at least one general patent application, the mean of the climate patent ratio increases to 6%. The average number of general patents for suppliers is 11.20, while the average 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 4 (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

reporting company, including both upstream and downstream emissions.

[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.

[18]This figure differs from the summary statistics shown in Table 2, Panel A because the variable in the table (number of general patents) takes the natural logarithm. The climate patent ratio is lower (but still in the same order of magnitude) than the mean green patent ratio (11%) reported in Bolton et al. (2023), related to the fact that Bolton et al. (2023) focus on worldwide patents where the ratio of climate patents to general patents is larger than for USPTO patents that we examine.

and 2.52 existing customers in a fiscal year.

3 Climate Innovation and Customer Carbon Emissions

3.1 Main Results

In this section, we explore whether climate innovation by suppliers has an impact on reducing GHG emissions of customer firms along the supply chain. This analysis complements the work of Bolton et al. (2023) who primarily focus on the potential CO2 emission reductions achieved by the innovating firms themselves. We argue that the primary beneficiaries of climate innovation are often the customers of products incorporating the climate technology. This idea becomes important in light of our finding in Table A1 that almost 70% of US climate patents are granted for product innovations. This implies that the majority of new climate technologies are integrated into products and that carbon emission reductions should overwhelmingly occur at the customers rather than the innovating firms themselves. However, it is essential 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 CO2 emissions savings may be even 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 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 measures for customer emissions, by distinguishing between Scope 1 (direct) and Scope 2 (indirect, energy-related) emissions and by calculating total emissions (tons of CO2) and emissions intensity (total emissions divided by firm output) according to Bolton and Kacperczyk (2021a, 2022).[19]

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

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.[20] We replicate Bolton et al. (2023)'s definition of our main independent variable, supplier's climate patent ratio, 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. 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 (this follows Bolton et al. (2023)). Besides, we also control for the number of suppliers as well as the CO2 emissions in year t. Additionally, 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 estimations, our first main result. In Panel A, we consider Scope 1 emissions. We standardize the supplier's climate patent ratio with a standard deviation of 1 and scaled the coefficients by 100. As shown in Panel A, a one-standard deviation increase in the supplier's climate patent ratio corresponds to a reduction of roughly 10.7% in total emissions (Scope 1) and 12.5% in emission intensity (Scope 1) over the subsequent five years. These figures translate into a decrease of 47,813 tonnes (446,858 $\times$ 10.7%) of CO2 and 6.19 tonnes per million dollars output (49.55 $\times$ 12.5%), respectively.

We then look at Scope 2 emissions in Panel B. It is important to note that there is no clear a priori expectation regarding the changes in Scope 2 emissions. For instance, if a company replaces traditional vehicles with electric cars from Tesla, its Scope 1 emissions might decrease, yet there could potentially be an increase in Scope 2 emissions. Conversely, if this company invests in solar panels or utilizes green building materials, both its Scope 1 and 2 emissions are anticipated to decrease. This caveat notwithstanding, 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 with a 5.54% decrease in total emissions (Scope 2) and a 6.08% decrease in emission intensity (Scope 2).

Notably, Panel A and Panel B also show that there is no significant reduction in CO2 emissions when the number of general patents granted to a supplier increases, indicating that the impact is specific to climate-related technologies.

[20] Climate patent ratio is set to zero if the supplier has no patents filed in year t.

We find similar results when using the number of climate patents instead of the climate patent ratio, as we show in Table A3 in the Online Appendix. One particular concern is that suppliers with a high climate patent ratio might be small innovators. For instance, if a firm has only one patent and that patent is climate-related, the climate patent ratio would be 1. However, this concern does not arise 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. Additionally, the pairwise correlation between the climate patent ratio and the number of general patents is 0.02, which is close to zero.

We also split the sample according to the NAICS 2-digit industries of the customer companies. Table A4 in the Online Appendix shows that the impact of climate technology on Scope 1 emission reductions is strongly significatoin in coal mining (NAICS: 20 and 21), manufacturing (31, 32 and 33) and transportation (48 and 49). In contrast, there are no significant effects in the service industries, consistent with the fact that coal mining, manufacturing and transportation are the sectors with the highest direct CO2 emissions.

We also examine the role played by differences between technology sector, using the Y02 subcategories. As documented in Table A5, climate patents in renewable energy and energy efficiency (Y02E), building technology (Y02B), and transportation (Y02T) exhibit the most robust impact, progressively growing over a five-year time frame. These three 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 higher emission intensity (see the discussion of Table 4 below.) and with the analysis in IEA (2021), forecasting that these particular climate innovation categories hold the greatest potential for fostering accelerated decarbonization. In contrast, we observe a comparatively weaker and less consistent impact within the highly active domain of information and communication technologies (Y02D). Additionally, for carbon capture and storage (CCS, Y02C), where the patent sample size is notably small and concentrated, caution is warranted in interpreting the resulting impact. Our analysis reveals no discernible effect on customer emission reductions concerning the production processes of goods (Y02P), a somewhat unexpected finding.

3.2 Extensions

In the preceding section, we use a weighting method for suppliers based on their relative importance to the specific customer firm, calculated as the supplier's sales to the customer divided by the total sales from all suppliers. However, with this approach we lose approximately 90% of the observations due to missing sales data within the supply chain relationships. To address this limitation, our first empirical model extension, in line with Kale and Shahrur (2007), adopts an alternative method. Here, we use the supplier's firm-level sales data (from Compustat) instead of the specific supplier-to-customer sales as the basis for weights. Our empirical 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 that supply chain relationships accompanied by sales information might hold greater significance for both the supplier and the customer. Within the supply chain literature, these relationships are often categorized as dependent suppliers, reliant on a customer for a substantial portion of their revenues (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. Overall, climate technology is not a silver bullet, but an important tool for reducing GHG emissions along the supply chain and for those high-emission customer firms.

In Panel C of Table 4, we distinguish between climate product patents and climate process patents. In general, 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 CO2 emissions at the innovator firm (in unreported regressions, we find no significant effect of process innovations on innovator or customer emissions.)

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

There are obviously endogeneity issues, and specifically concerns about selection effects between customers and suppliers are still not yet eliminated. It is plausible that customer firms with more ambitious decarbonization goals are also more likely to select green suppliers with a climate innovation agenda, even if the supplier's climate innovation success makes no direct causal contribution to the customer's CO2 reduction, so that we observe a misleading association due to simultaneity bias.

To address this concern, we conduct regressions on a supplier × customer × year sample. Each observation in this sample represents a supplier selling products or services to a customer in a specific year (t).[21] We include supply chain relationships with missing sales in our analysis.

The regression results, presented in Panel D of Table 4, use the customer's forward-looking Scope 1 CO2 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 demonstrate that, for a stable supplier-customer pair, the customer's CO2 emissions respond to the supplier's newly granted climate patents. The coefficients in Panel D are significantly negative, indicating a negative relationship. However, the magnitudes of the coefficients are smaller than those in Table 3, as we treat each supplier-customer relationship equally, disregarding the varying importance of different suppliers to specific customers. We obtain similar results for Scope 2 emissions in Panel E.

We emphasize that there may still be residual endogeneity issues. It is likely that customers with intentions to reduce their carbon footprint might prompt their suppliers to engage in greater climate innovation. This observation does not refute our premise that climate innovation contributes significantly to CO2 emission reductions within the supply chain. However, disentangling the primary motivation behind climate patent inventions—whether initiated by suppliers or driven by customer demands—presents a complex challenge. In Section 5, we introduce a method of exogenous shocks to the supplier's climate innovation and patenting activity, based on technology obsolescenceof climae knowhow and on random assignments of patent reviewers. As we will discuss later, the outcomes in Table 10 highlight that as a supplier's past climate innovation knowledge becomes obsolete, the likelihood of generating new, high-quality climate innovation diminishes, consequently leading to higher emissions for the customer firm. This key finding substantially alleviates concerns suggesting that it is solely the customer's desire to reduce CO2 that drives suppliers to generate new climate innovation.

Finally, in theory, customer emissions should also be measured by the downstream Scope 3 emissions reported by the supplier firm. Scope 3 emissions contain all indirect emissions (not included in Scope

[21] Schiller (2018) uses a similar approach.

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 A7. 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 according to Klaaßen and Stoll (2021); They find that reported Scope 3 data in the tech sector omit half of actual Scope 3 emissions.

4 Knowledge Diffusion and New Business Customers

In this section, we turn to our second main inquiry, the relationship between climate innovation and knowledge diffusion at the extensive margin, via the acquisition of new customers. This is a natural (but understudied) follow-up question to an investigation of how innovation percolates through supply chain networks. It is arguably particularly relevant for climate innovation given the urgency to reduce GHG emissions and the global public goods character of widespread adoption of successful Y02 patents.

It is not a foregone conclusion that climate innovation will facilitate business expansion and the acquisition of new customers, or "business stealing". Fowlie (2010) documents that reducing GHG emissions is costly and therefore not clearly a profit-boosting decision. In response, suppliers are likely to charge a premium for their climate innovation and they may also try to increase their margin to benefit from their innovation. As a result, demand may be stifled by price increases, and the net effect (given the customer interest in the new CCMT) is not obvious. 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 increased demand and consumer willingness-to-pay for greener products. For example, Schiller (2018) finds that suppliers with high ESG ratings attract more customers from countries with stringent ESG standards. Second, there is growing interest in sustainable investments (Hartzmark and Sussman, 2019; Ardia et al., 2022) and financial markets increasingly tend to incorporate carbon transition risk into security prices, resulting in a lower cost of capital for firms with lower transition risk (Chava, 2014; Bolton and Kacperczyk, 2022; Pástor, Stambaugh, and Taylor, 2022). For both reasons, companies should increasingly be willing to pay a premium for products that incorporate new climate technology.

In this section, we tackle these questions from two different angles. We first look at the reaction from the customer's perspective of supplier choice among a well-defined set of potential suppliers. We then consider suppliers and analyze their capacity for business expansion by increasing the number of customers in the wake of climate innovation.

4.1 Customer's Choice of New Suppliers: Discrete Choice Model

We develop a discrete choice model (McFadden, 1974) that portrays each customer's selection of suppliers as a choice among a set of potential suppliers to investigate the role of climate innovation in this selection and to answer the question of whether a typical customer prefers suppliers with more climate innovation.[22]

For each customer firm that has at least one supplier in a given year, we create a set of alternatives, which includes two types of suppliers. The first type consists of the suppliers that are selected by the customer firm. The second type includes suppliers that offer similar products to the chosen suppliers but are not selected by the customer firm. We use Hoberg and Phillips (2016)'s text-based product description measures to obtain the second set of suppliers (not selected). The final regression sample is at the level of customer × potential supplier × year. The model uses the baseline regression,

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

where the dependent variable $\mathrm{I(Select)}_{c,s,t}$ is a dummy that equals one if the customer firm c selects the supplier s to establish the supply chain relationship in year t. In this discrete choice model, we can control for the firm characteristics of both suppliers and customers, as well as their interactions. Our model differs from a standard textbook discrete choice model in two important ways. First, a standard textbook-based discrete choice model requires exclusivity among alternatives, i.e., only one alternative can be chosen at a time. In contrast, a typical customer can choose simultaneously multiple suppliers in the same fiscal year. Second, we estimate the model using OLS instead of conditional logit because we introduce complicated two-way and three-way interactions. The interaction term is much harder to explain in a logit model (Ai and Norton, 2003).

[22] In principle, the establishment of supplier-customer relationships involves a two-sided matching process. However, customer firms tend to have significantly greater bargaining power. According to Schiller (2018), the average customer firm is ten times larger than the average supplier in terms of the book value of assets and five times larger in terms of market capitalization.

Table 5 reports the estimation results. In column (1), the coefficient of the supplier's climate patent ratio is positive and highly significant, implying that customers in general 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. The strongly significant and positive coefficient also underlines the validity of our empirical approach which is novel in the innovation and in the supply chain literature. As an aside (since beyond the topic of this paper), to the best of our knowledge we are the first to document such a business expansion effect (acquisition of new customers) following supplier patents in general (a similar analysis of dynamic supply chains reaction to innovation is absent in the literature).

Column (2) of Table 5 breaks the sample period into two sub-periods, before and after 2010. It reveals that the effect, while seemingly significant for the full sample, is really explained only by climate patents with application date starting in 2010. Only the coefficient on the supplier's *climate patent ratio* $\times$ I(Post 2010) is positive and significant, again showing that 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(Post 2010) and supplier's *number of general patents* $\times$ I(Before 2010). This shows that the structural break around 2010 only matters for climate patents. We discuss this structural break in the next section, after introducing our second empirical approach that provides more evidence on the regime change around 2010.

We then explore the heterogeneous impact of climate innovations on different types of new customers. An important advantage of the discrete choice model is that we can control for the firm characteristics of both suppliers and customers, as well as their interactions. Table 5 column (3) shows that the interaction term between the supplier's climate patent ratio and the customer's environmental 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 general 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). It shows that the stronger preference is not true for customers with high governance or social scores. Moving to column (5), we can conclude that the stronger preference for the supplier's climate technology by customers with a high E-score exists only after 2010, as shown by the triple interaction term (interacting with I(Post 2010) and I(Before 2010)).

Similarly, in columns (7) and (8) of Table 5, customers with high emissions (either measured by total emissions or by emission intensity) are more likely to choose climate-innovative suppliers.[23] Again, this supplier-customer combination is more frequent after 2010, but not before 2010.

4.2 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 supplier's perspective and its capacity to attract new customers. We construct our sample of potential suppliers following Section 2.4 and then run the following regression,

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

The dependent variable (Num_New_Customer_Firms) counts how many *new business customers* purchase products or services from firm i in year t.[24] We lag the climate patent ratio by one year and interact it with $\Big\{I(\text{Year})_t\Big\}_{Year=2005}^{2021}$, a set of dummies equal to 1 in year t. The interaction helps us study the possibly time-varying effect of climate innovation on attracting new customers. Moreover, we also control the number of general patents measured in year t-1.[25] We plot the coefficients of $\beta_{1,\text{Year}}$ as well as their confidence intervals at the 90% level in Figure 1. In the online appendix (Figure A1), we conduct robustness checks using the Poisson regression and find similar results.

Figure 1 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% – 22.06% increase in the number of new business customers. In contrast, the coefficients before 2010 are insignificantly different from zero.

Although we find a strong structural break in 2010 in our regression analyses, we cannot pinpoint

[23] We also add the interaction between customer's firm size and supplier's climate patent ratio since the firm size is highly correlated with the total CO2 emissions.

[24] A new customer is defined as a customer that has never bought products from firm i before and start buying in year t.

[25] $\mathbf{X}_{i,t}$ 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.

the causes because there are several concomitant developments around 2010. First, it 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, patent information related to CCMT was scattered throughout many IPC and CPC categories and did not fall under a single classification section, making it difficult for non-technology specialists to identify them (Angelucci et al., 2018). The introduction of the "Y02" scheme helped stakeholders including customer firms to quickly screen for climate-relevant patents. Second, there were other simultaneous initiatives to enhance climate patent impact. For example, on December 8, 2009, the USPTO implemented the Green Technology Pilot Program, which allows patent applications related to environmental quality, energy conservation, development of renewable energy resources, and reduction of greenhouse gas emissions to be advanced out of order for examination and to get accelerated review. Third, the failure of the December 2009 Climate Change Conference (COP15) to produce a new, long-awaited global climate agreement had the effect of a shock that significantly raised public attention to climate change (Ardia et al., 2022). Lastly, there are papers on market reactions to climate news that 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.

To further examine the 2010 structural break, we plot the annual median market value of climate and non-climate patents separately in Figure 2.[26] 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.[27] For climate patents, we only include Y02E (renewable energy and energy efficiency) and Y02C (carbon capture and storage) because the original Y02 tag only includes these two categories in 2010 (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, and a similar magnitude of jump does not exist for non-climate patents. This implies that Y02 is not only attracting the attention of customers but also that of investors. Interestingly, we don't find a similar 2010 jump for other Y02 categories.

Next, we explore the role of customer heterogeneity from the innovator's perspective, asking what types of customer firms it can more likely attract after s climate patent grant. Table 6 answers this

[26] We plot the median instead of the mean to avoid the effects of outliers.
[27] Data on the market value of patents are downloaded from Kogan et al. (2017).

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) of Panel A, the dependent variable remains the same as in Figure 1 and is defined as the number of new customers attracted by firm i. In addition, we perform a median split of all given new customers in a given year using their environmental scores (see Section 2.3). In columns (2) and (4) ((3) and (6)), the dependent variable counts only those newly acquired customers with environmental scores above (below) the median. Table 2 Panel B shows that the summary statistics are very similar between the number of new customers with high and low environmental scores. Moreover, we add the interaction terms between the climate patent ratio (measured in year t-1) and two dummies for the periods before and after 2010, in response to the finding of a structural break in Figure 1. 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 confirm the previous findings in Figure 1 that climate innovation helps to attract new business customers only after 2010, but not before 2010. Moreover, only the coefficients on the regression of the number of new customer firms with a high environmental score are positive and significant, suggesting that climate technology attracts new customers with high environmental scores. A high environmental score could be a proxy for firms' preference for environmental and climate change concerns, i.e. indicate firms that are more willing to buy and pay for climate innovation products,[28] a corporate preference that, as first explained in Bénabou and Tirole (2010) and explored in a growing literature on ESG (or CSR) preferences, could be related to various motives, such as an intrinsic belief of decision-makers in "doing well by doing good" (Baron, 2001) or express preferences of company stakeholders.

In Panel B, we conduct a similar sample split for all customer firms in a given year but use a measure of environmental supply chain management from LSEG ESG, a variable that LSEG (formerly Refinitiv) constructs as a measure whether a customer firm considers environmental impacts when selecting its suppliers.[29] As shown in the coefficients of Panel B, supplier's climate innovation significantly attracts

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

[29] We drop customers where the measure of ESG supply chain management is missing.

new customer firms that are committed to environmental supply chain management, but again, only after 2010.

In Panel C, we perform another sample split by annual CO2 emissions of customers. We use the sum of Scope 1 and of Scope 2 emissions (in tons). We do not make any within-industry adjustments for CO2 emissions, following Bolton and Kacperczyk (2022)'s view that raw and total carbon emissions better capture a firm's carbon transition risk. Similarly, Choi et al. (2022) use industry-level emissions measures in their analyses. Interestingly, in Table 6 Panel C, we find that new customers attracted by a supplier's climate technology are those with high CO2 emissions. In contrast, firms with relatively low emissions are less likely to purchase products from climate innovation suppliers, as shown by the negative coefficients of the climate patent ratio $\times$ Post 2010 in columns (3) and (6).

How do we explain this result in Panel C? High-emission firms are not necessarily those with low environmental scores. Table 2 Panel D shows a very low pairwise correlation between the components environmental score and CO2 emissions.[30] Customers with high carbon footprints may prefer climate-innovative suppliers because their product innovations may produce the biggest emissions impact. In fact, we have documented evidence consistent with this view in Section 3.

It may appear curious that high-emission firms reveal in their supplier choice a strong willingness to pay for technology that reduces their GHG emissions, given that their past trajectory of high emissions may betray insouciance about their carbon footprints. The evidence is, however, consistent with the finding of Cohen et al. (2021) that high-emission firms are also large climate innovators themselves. Also, climate-conscious institutional investors may reserve their strongest pressure in favor of decarbonization towards high emission firms (Atta-Darkua et al., 2022). In addition, higher carbon emissions lead to higher costs of capital (Bolton and Kacperczyk, 2021b), providing an extra financial incentive to clean up for big carbon emitters.

[30] We find a slightly positive correlation, consistent with similar findings in Boffo, Marshall, and Patalano (2020). There are two possible explanations for the low correlation. First, while ESG ratings are calculated within each industry, CO2 emissions are measured as the absolute level. Second, environmental scores in ESG ratings typically include much more information than GHG emissions, such as water scarcity, waste management, and biodiversity issues.

4.3 Existing Customers and Operating Performance

We now turn to the choices of the supplier's (and climate innovator's) existing customers. Will they remain loyal or, possibly as a result of higher costs, switch to another supplier? Table 7 Panel A regresses the number of existing customers who stop buying products from the given supplier. It shows that existing customers do not tend to desert climate innovators, as all coefficients in the three columns are far from significant.

In summary, suppliers' climate innovations help suppliers to attract new customers, but do not drive away old customers. These effects could ultimately lead to sales growth and profit improvements because climate-innovative products may command a higher premium. As a result, Table 7 Panel B examines how climate innovation affects suppliers' operating performance. In column (1) of Table 7 Panel B, the dependent variable is the natural logarithm of sales. Consistent with our intuition, the coefficient of the climate patent ratio (t-1) $\times$ after 2010 is positive and significant. Climate innovation is associated with sales growth only after 2010. In columns (2) and (3), we examine ROA and profits separately, where the variable (profits) is defined as (total sales $-$ cost of goods sold)/(total sales). Interestingly, the coefficients of the climate patent ratio (t-1) $\times$ before 2010 are both negative and significant, while the climate patent ratio (t-1) $\times$ after 2010 is positive (but not significant). Our results are consistent with recent findings by Bolton et al. (2023) that the climate patent ratio predicts declining market shares and profits. Our explanation is that this only happens before 2010, when climate technology is not widely recognized. After the introduction of the "Y02" tag by the EPO and the United Nations, firms with more climate innovations do not suffer from lower ROA and profits.

4.4 What Types of Climate Patents Attract Customers?

In this section, we begin to explore the heterogeneous impact by differentiating between various types of climate patents. More specifically, we ask which subsets (types) of climate innovation has the strongest pull effect in attracting on new customers. Inspired by the canonical innovation literature (see Cohen (2010)), we differentiate climate innovations by their quality. Although the literature uses patent citations to measure patent quality (Jaffe and Trajtenberg, 2002), the citation measure faces a substantial stumbling block in the context of our study. Since our climate patent sample spans from 2000 to 2021, many recent-approved patents have not yet received citations by the end of our sample periods (Lerner and Seru, 2021).

As a result, we measure the importance of a given patent using Kogan et al. (2017)'s measure of the market value of patents. Kogan et al. (2017) estimate the economic value of patent j as the product of the estimate of the stock return due to the issuance 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.[31] In Table 8 Panel A, we construct two new measures, Climate Patent Ratio (High Value) and Climate Patent Ratio (Low Value). The Climate Patent Ratio (High Value) is equal to the number of new climate patents (invented by firm i in year t) of which the market value is higher than the annual median market value of all climate patents divided by the total number of general new patents invented by firm i in year t. The dependent variable in Table 8 is still the number of new customers acquired by a given supplier. We distinguish these new customers along two dimensions: E-score and the emission level. The coefficients of Table 8 Panel A show that high-value climate patents dominate the attraction effect of climate innovation.

Another dimension is the extent to which a given climate patent is essential in producing the final products that the supplier (the innovator) sells to customers. Cohen, Gurun, and Kominers (2019) argue that many patents can be of great strategic value but of no production value to the patent holders. Unfortunately, the literature on innovation is rather silent on linking each patent to the patentee's products. Therefore, we contribute by constructing a new measure.

We use a new 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 cosine similarity naturally means the 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.[32] Figure 3 shows an example of our pairwise document similarity.[33]

[31] Data on the market value of patents are downloaded from Kogan et al. (2017).

[32] 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).

[33] The climate patent is entitled "Enhanced Queue Management For Power Control Of Data Storage Device". The patent is classified as a climate patent because it has a Y02D tag. The patent is granted to Western Digital Corporation, and we then download 10-K Item 1 for the company in the same year as the patent application. The Stanford GloVe model results in a 0.93 correlation for this example.

Table 8, Panel B, reports our results. 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. The Climate Patent Ratio (High-Related) is equal to the number of new climate patents (invented by firm i in year t) 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 invented by firm i in year t. Panel B shows that only climate patents that are highly correlated with the supplier's products attract new customers.

5 Endogeneity: Instrumental Variables Strategies

Thus far, our analysis has unveiled two key findings: first, suppliers' climate innovation significantly aid their customer firms to reduce CO2 emissions. Second, customer firms exhibit a significant inclination to pick suppliers engaged in climate innovation. Thus, one incentive channel for firms to engage in climate innovation is their capacity to attract new customers, particularly customers with commendable environmental standings and higher emissions. Nevertheless, our study faces difficult potential endogeneity challenges that could undermine these main findings. For instance, it is plausible that various ESG-related firm-level policies, rather than solely the climate patent ratio, serve as magnets for new business customers. Moreover, these ESG-related policies might be interrelated with climate innovation policies, introducing complexities in interpretation. Concerns about selection effects and simultaneity further compound these challenges. To mitigate the risk of omitted variable bias, we introduce two distinct instrumental variables. These instruments introduce exogenous shocks to the supplier's climate patents, offering a robust framework for addressing endogeneity concerns.

In Section 5.1, we introduce the concept of patent examiner leniency (Sampat and Williams, 2019; Farre-Mensa et al., 2020) and apply it to climate patents. Section 5.2 uses technology obsolescence (Ma, 2022) to shock the innovation ability of climate inventors.

5.1 Patent Examiner Leniency

Our first identification strategy exploits quasi-random shocks in the probability of patent approvals. The patent 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 (Cockburn et al., 2002). Moreover, in most USPTO technology art units, patent examiners are assigned to patent applications in a quasi-random fashion (Sampat and Williams, 2019; Farre-Mensa et al., 2020).[34] As a result, we utilize the patent examiner leniency as an instrumental variable (IV) for the number of climate patents issued to a supplier firm. Since the examiners are randomly assigned, the leniency metric is likely to be orthogonal to any remaining ESG-related firm practices (other than climate patents) that aid in attracting new customer firms.

Specifically, 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, conversely, faces strict scrutiny for their non-climate patent application, the resulting *climate patent ratio* for this firm is highly likely to be elevated. We separate each firm's patent applications into climate-related and non-climate-related applications. The Examiner Leniency Diff. is defined as,

$$\text{Examiner's Leniency Difference}_{i,t} = \frac{1}{N_{clim}} \sum_{p \in \text{Clim}}^{N_{clim}} [\text{Examiner Leniency}_{p,e}] - \frac{1}{N_{non\text{-}clim}} \sum_{p \in \text{Non-Clim}}^{N_{non\text{-}clim}} [\text{Examiner Leniency}_{p,e}] \quad (6)$$

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 Leniency$_{p,e}$ is the leniency of the examiner e who reviews the given patent application p. Specifically, it is constructed as

$$\text{Examiner Leniency}_{p,e} = \frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1} - \frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1} \quad (7)$$

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

[34] Patent applications are assigned to art units of patent examiners by technological specialization. There are about 900 art units, so they are a fairly granular subdivision of the patent examination process.

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.

Columns (1) and (2) in Table 9 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). Importantly, the strong F-tests indicate that there is no significant concern about weak instrumental variables in our study.

The second-stage regressions in the remaining columns of Panel A are presented. Consistent with our prior analyses, we consistently incorporate two interaction terms between the climate patent ratio and dummies for 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)). Similarly, Panels A and B perform sample splits using the environmental supply chain policy dummy and total GHG emissions (Scope 1+2), respectively.

In summary, our findings corroborate results akin to Table 6: (i) Supplier's climate innovation becomes a catalyst for attracting new customers post-2010; (ii) Climate innovation acts as a significant magnet for new customers, particularly those with high environmental scores and elevated emissions. These outcomes notably alleviate concerns regarding omitted variable bias and bolster the case for a causal imterpretation.

5.2 Technology Obsolescence

A potential limitation of the examiner leniency instrument is that it relies on random variation in patenting probabilities, but does not incorporate exogenous variation in a firm's innovative ability. We therefore introduce our second instrument, technology obsolescence, which relies on the second type of variation and is constructed along the lines of Ma (2022). The rationale is that knowledge itself becomes increasingly obsolete, and as a climate innovator's knowledge ages, the innovator is less likely to be at the frontier of climate technology and to produce relevant innovations for its customers. Crucially, the depreciation of a firm's knowledge stock, as measured by technology obsolescence, depends on the rate of innovation of other firms, and is therefore usually caused by unexpected technology shocks outside the firm's boundary. Thus, the obsolescence metric should measure technology shocks (such as leaps caused by disruptive innovation) that are likely orthogonal to the innovator's own policies and decisions to attract new client firms through climate patents. Additionally, this variable exhibits no correlation with the demand from customer firms, urging suppliers to elevate their climate innovation activities. It helps to sharpen the causality that climate innovation does reduce CO2 of customer firms. In support of this interpretation, Ma (2022) shows that technology obsolescence overwhelmingly measures technology-specific shocks that vary widely within each firm, not firm-specific variation.

Thus, we construct a new instrumental variable, technology obsolescence, to strengthen the case for a causal relationship between climate innovation, customer CO2 emissions and the attraction of new customers. To do so, we partition each firm's patent stock (cumulative and historical patents applied up to year t) into two categories: climate-related and non-climate-related patents. Our aim is to concentrate on the specific obsolescence of climate patents while controlling for the inherent variation in general technology obsolescence among firms. To achieve this, we employ the disparity in technology obsolescence between climate and non-climate innovations as an instrument for the key independent variable, the *climate patent ratio*.

Specifically, our pivotal variable, $Tech\_Obsolescence\_Diff$, is defined as:

$$\begin{aligned} Tech\_Obsolescence\_Diff_{i,t} = {} & \text{Tech\_Obsolescence(Climate Patent Stock)}_{i,t} \\ & - \text{Tech\_Obsolescence(Non-Climate Patent Stock)}_{i,t} \quad (8) \end{aligned}$$

where $\text{Tech\_Obsolescence(Climate Patent Stock)}_{i,t}$ $\left(\text{Tech\_Obsolescence(Non-Climate Patent Stock)}_{i,t}\right)$ captures the obsolescence measured in the year-t period for past climate technologies (all other past non-climate innovation) invented by firm i. We calculate technology obsolescence following the approach outlined in Ma (2022). Specifically, firm i's climate patent stock in year t includes all (Y02) climate patents applied by firm i up to and including year $t-5$. The knowledge space of this climate patent stock comprises all third-party patents (including non-climate patents) cited by the patents in this climate patent stock set. Subsequently, we compute the annual citations in year $t-5$ and in year t within this knowledge space. Finally, Technology Obsolescence is determined as the difference between both citation measures:

$$\begin{aligned}\text{Tech\_Obsolescence(Climate Patent Stock)}_{i,t} = {} & \text{Num\_Cite}_t(\text{Knowledge Space(Climate Patent Stock}_{i,t})) \\ & - \text{Num\_Cite}_{t-5}(\text{Knowledge Space(Climate Patent Stock}_{i,t}))\end{aligned} \tag{9}$$

We establish the measure of $Tech\_Obsolescence$ for the non-climate patent stock accordingly. The first-stage regression, documented in Column (1) of Table 10 Panel A, demonstrates a significant negative association between $Tech\_Obsolescence\_Diff$ and the climate patent ratio, with the coefficient statistically significant at the 1% level. Subsequent columns in Panel A present the results for the second-stage regressions. Consistently, these findings reaffirm that climate innovation plays a pivotal role in attracting new business customers, in line with our evidence for the Examiner Leniency instrument. Moreover, the results highlight that this effect holds significant weight for customers exhibiting either high environmental scores or high initial GHG emissions, measured in year t-1.

To bolster the case for a causality interpretation, we replicate our methodology used in Table 4, specifically Panels D and E, and construct a supplier-customer pair sample with pair fixed effects, but we conduct reduced-form 2SLS regressions. The results are presented in Panel B of Table 10. The positive coefficient observed for $Tech\_Obsolescence$ indicates that as a supplier's past climate innovation knowledge becomes obsolete, the likelihood of generating new, high-quality climate innovation diminishes, subsequently leading to higher emissions for the customer firm. This finding substantially alleviates concerns suggesting that it is the customer's desire to reduce CO2 emissions that drives suppliers to generate new climate innovation. In summary, our reduced-form 2SLS findings are consistently aligned with our suggested interpretation for the results in Tables 3 and 4.

6 Conclusions

Most observers agree that a successful transition to net zero within a few decades will not be possible without major technological advances. However, there is no micro-level evidence so far that climate innovation is indeed effective in reducing GHG emissions. On the contrary, there are concerns that substitution or rebound effects may dominate any technology gains (Bolton et al., 2023).

In this paper, we study the emission and business expansion impact of climate innovation (identified with the "Y02" scheme), focusing on the innovator's downstream supply chain network. Specifically, we ask (i) whether climate innovation invented by a supplier firm allows its customer firms to reduce CO2 emissions, and (ii) whether climate innovation facilitates the acquisition of new business customers.

We find that climate innovations help customer firms to reduce carbon emissions, and that the effect can be attributed to innovations embedded in the supplier's products. Emissions savings are accentuated for high-emission firms and firms with stronger environmental concerns. To study the extensive-margin dynamics of supply chains, we construct a discrete choice model of customer firms' choice of potential suppliers. We show that customer firms generally have a strong preference for suppliers' climate innovations. Moreover, we show that climate innovation allows suppliers to expand their customer base. We find that the capacity to attract new customers is more pronounced for customers with a strong preference for reducing their carbon footprint which are firms with a strong preference for environmental protection, measured by their high environmental scores in their ESG ratings, or firms with elevated GHG emissions that presumably anticipate regulatory or investor pressure to curtail their GHG emissions. In summary, we find that climate innovation can be effective in reducing carbon emissions along the supply chain and influence the dynamics of supply chain relationships.

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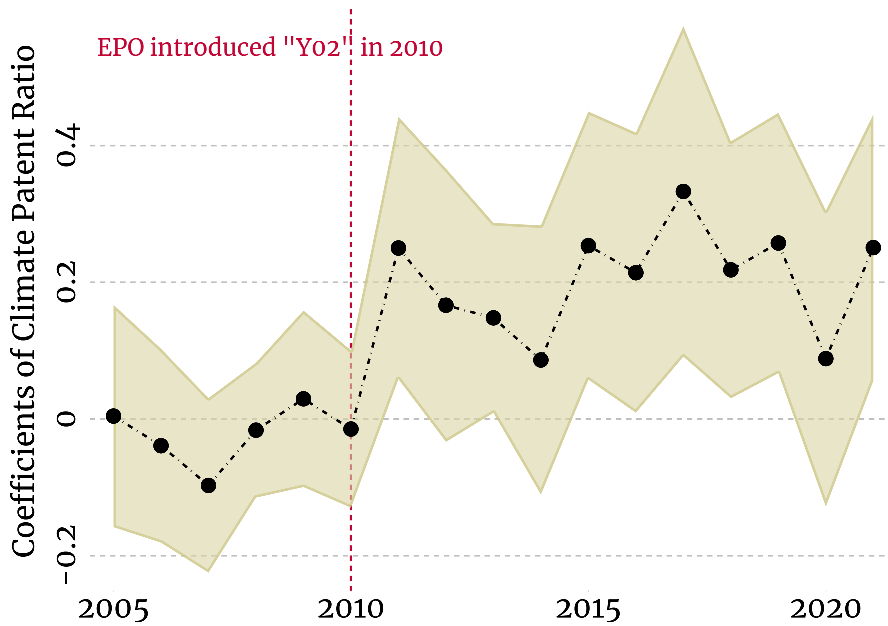
Figure 1. Supplier's Climate Patent Ratio and Number of New-Attracted Customer Firms

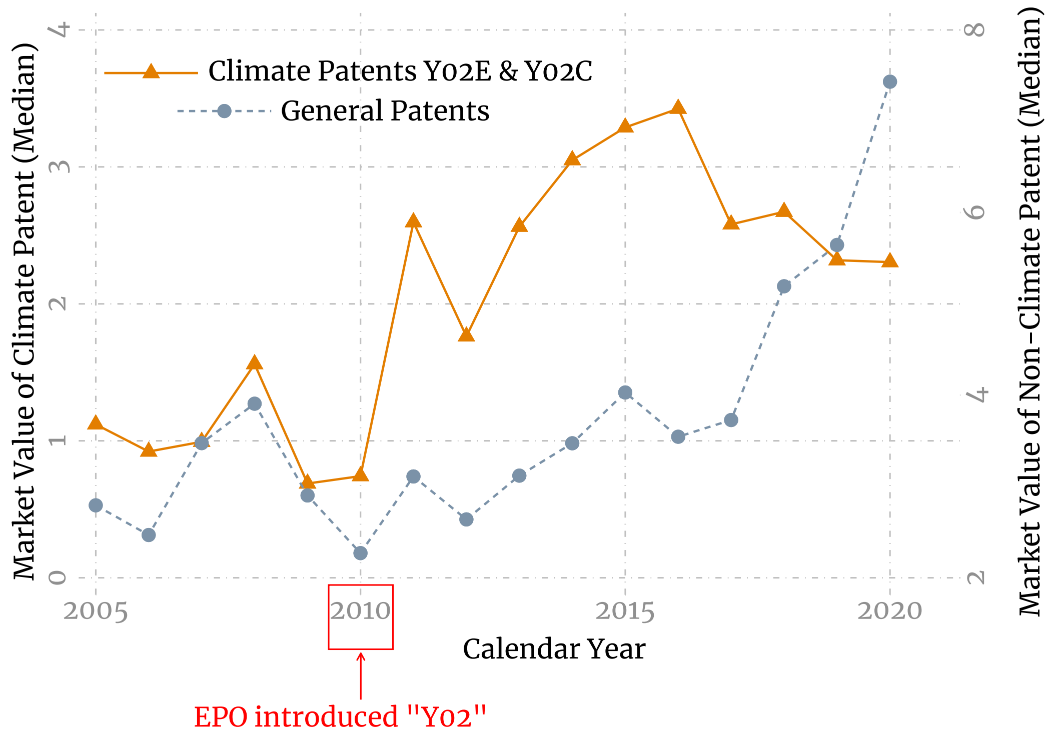


This figure examines the relationship between the climate patent ratio and the number of new customers attracted by each supplier firm. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

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

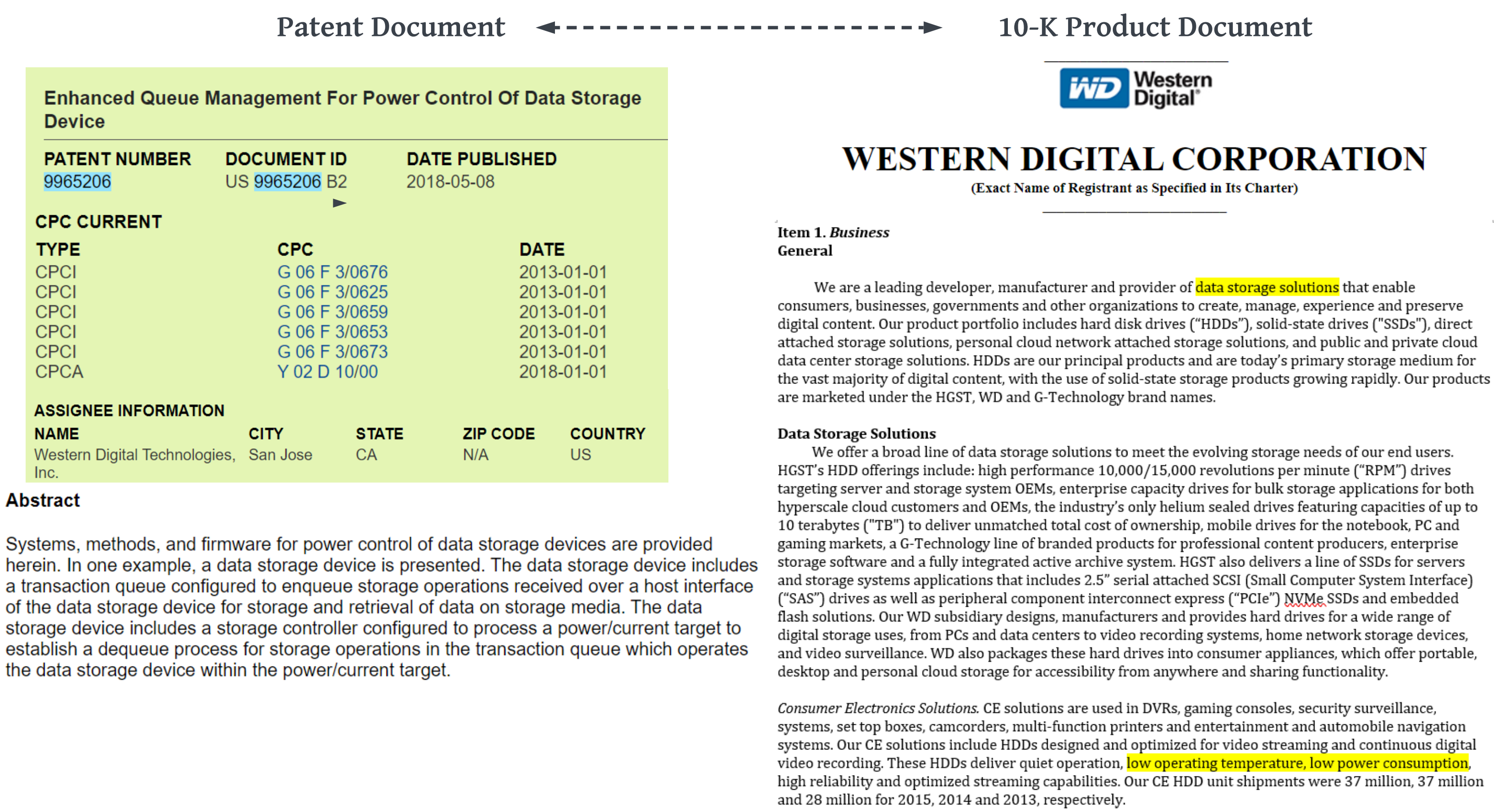
Where $Num\_New\_Customer\_Firms_{i,t}$ signifies the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. The dependent variable is transformed using the natural logarithm of $(1 + x)$. The variable $Clim\_Patent\_Ratio_{i,\mathbf{t-1}}$ represents the ratio of climate-related patents (Y02) newly invented by the firm to all patents invented by the same firm in year $t - 1$. The regression model encompasses 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 2. 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.

Figure 3. Patent to Product Relatedness for Climate Innovation



This figure serves as an illustration of how we measure the relatedness between a climate patent and the products of the company that owns the patent. To obtain the content of the patent, we adopt the approach outlined in Kogan et al. (2021), which involves utilizing the title, abstract, and detailed description text of the patent. For product descriptions, we obtain information from 10-K filings, specifically Item 1 that pertains to the Business Description, following the methodology of Hoberg and Phillips (2016). To compute the pairwise text similarity between the climate patent text and the product description text, we employ the Stanford GloVe model (Global Vectors for Word Representation). In our calculations, we focus on nouns and incorporate TFIDF adjustments. For a more comprehensive understanding of the detailed procedures, please refer to Kogan et al. (2021). In the figure, we present an example where the climate patent is titled "Enhanced Queue Management For Power Control Of Data Storage Device". This patent is classified as a climate patent due to its Y02D tag. The patent is issued to Western Digital Corporation, and we subsequently download Item 1 of the company's 10-K filing for the same year as the patent application.

Table 1. Summary Statistics of Supplier-Customer Relationships

This table presents summary statistics based on our supply chain data at the level of supplier-customer relationships. To create 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%

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 Estate (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.

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 General Patent Number	0.769	0.000	1.099	2.639	1.305	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	0.340	0.000	0.693	1.099	0.584	41,777
Number of New Customer Firms (High E-score)	0.197	0.000	0.000	0.693	0.438	41,777
Number of New Customer Firms (Low E-score)	0.201	0.000	0.000	0.693	0.421	41,777
Number of Existing Customer Firms	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	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)	(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]	-2.184**	-2.269**	-4.128**	-3.953**	-6.252**	-6.359***	-8.154**	-8.116***	-10.743***	-12.456***
	(1.059)	(1.143)	(1.942)	(1.769)	(2.563)	(2.311)	(3.203)	(3.120)	(3.743)	(3.581)
Supplier's General Patent Number [t]	-0.140	-0.444	0.282	0.352	-0.139	0.291	-1.283	-1.152	-1.230	-1.144
	(1.016)	(1.023)	(2.113)	(1.946)	(3.042)	(2.734)	(3.958)	(3.610)	(4.781)	(4.640)
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]	-1.253	-1.065	-6.297***	-5.490***	-6.662**	-5.844***	-8.183**	-7.187**	-5.543	-6.084**
	(1.445)	(1.228)	(2.402)	(1.949)	(2.798)	(2.224)	(3.569)	(3.160)	(3.606)	(2.672)
Supplier's General Patent Number [t]	0.268	-0.242	1.707	1.176	1.554	1.438	1.246	0.559	-1.944	-2.041
	(1.177)	(0.980)	(1.921)	(1.538)	(2.722)	(2.031)	(3.700)	(2.709)	(4.651)	(3.585)
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 using alternative setups. In Panel A, we include supplier-customer relationships with both non-missing and missing supplier-to-customer sales information when constructing the customer sample and calculating 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 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). Panel D involves running regressions using a supplier $\times$ customer $\times$ year sample. The dependent variable is the customer's future Scope 1 CO2 emissions in year $t+k$. The climate patent number represents the ratio of newly invented climate patents in year t by the supplier in the supplier-customer pair. Standard errors are clustered at the firm level in Panel A to C and at the supplier-customer pair level in Panel D. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative Weighting Methods

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 $\times$ 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] $\times$ 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] $\times$ 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 $\times$ 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 $\times$ 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: Supplier-Customer Pair Sample

	(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 E: 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 5. 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 that has at least one supplier in a given year, the set of alternatives includes (i) those suppliers that are selected by the given customer firm and (ii) those suppliers with similar products that are not selected by the given customer. We use Hoberg and Phillips (2016)'s text-based network industry classification (TNIC) to obtain the second set of suppliers (not selected). 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)	
Supplier's Climate Patent Ratio [t-1] ×								0.004	

Customer's GHG Emissions (Total) [t] × I(Before 2010)								(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 6. 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, $Climate\ Patent\ Ratio_{t-1}$, 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. 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

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

Table 7. Climate Patent Ratio, Existing Customers, and Operating Performance

This table examines the impact of climate innovation on both existing customers and the innovator's own operating performance. Panel A focuses on the dependent variable, which is the number of existing customer 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. Panel B analyzes the dependent variables of sales, return on assets (ROA), and profits. The 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. Statistical significance is denoted by *, **, and *** for the 10%, 5%, and 1% levels respectively.

Panel A: Existing Customer's Leave			
	(1)	(2)	(3)
	Number of Existing Customer's Leave		
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

Panel B: Operating Performance			
	(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

Table 8. Climate Patent Ratio and New Customer Firms (Extension)

This table presents extensions of Table 6. 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 3. 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 9. 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,

$$\text{Examiner's Leniency Difference}_{i,t} = \frac{1}{N_{clim}} \sum_{p \in \text{Clim}}^{N_{clim}} [\text{Examiner Leniency}_{p,e}] - \frac{1}{N_{non\text{-}clim}} \sum_{p \in \text{Non-Clim}}^{N_{non\text{-}clim}} [\text{Examiner Leniency}_{p,e}] \tag{11}$$

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 Leniency$_{p,e}$ is the leniency of the examiner e who reviews the given patent application p. Specifically, it is constructed as

$$\text{Examiner Leniency}_{p,e} = \frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1} - \frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1} \tag{12}$$

$\frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1}$ 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.

Panel A: Split Customer Firms 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: Split Customer Firms by GHG 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 10. Climate Patent Ratio and New Customer Firms (Technology Obsolescence as Instrument)

This table examines the association between the number of new customer firms that purchase goods or services from suppliers and the suppliers' climate patent ratio in a 2SLS-regression setup. Column (1) shows the 1st stage regressions, and columns (2) – (5) tabulate the 2nd stage regressions. The sample ranges from 2011 to 2021. We use the difference in technology obsolescence between climate and non-climate innovation to instrument the key independent variable, the climate patent ratio. Specifically, the Tech. Obsolescence Diff. is defined as,

$$\text{Tech. Obsolescence Diff.}_{i,t} = \text{Tech. Obsolescence(Climate Innovation)}_{i,t} - \text{Tech. Obsolescence(Non-Climate Innovation)}_{i,t} \tag{13}$$

Tech. Obsolescence(Climate Innovation)$_{i,t}$ captures the year-t level of obsolescence for the climate technologies invented by firm i. We calculate the tech obsolescence following Ma (2022). The set of climate technologies for firm i in year t is defined as all climate patents (Y02) invented by firm i before and up to year $t-5$. Then, the knowledge space of this set of climate tech contains all third-party-filled patents (including non-climate patents) cited by firm i's climate patents before $t-5$. Finally, we calculate the annual citation change between year t and $t-5$ for this set of knowledge space.

$$\begin{aligned}\text{Tech. Obsolescence(Climate Innovation)}_{i,t} = {} & \text{Num Cite}_t(\text{Knowledge Space(Climate Innovation}_{i,t}))- \\ & \text{Num Cite}_{t-5}(\text{Knowledge Space(Climate Innovation}_{i,t}))\end{aligned} \tag{14}$$

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: Attract New Customer Firms

	(1)	(2)	(3)	(4)	(5)
	First Stage	Second Stage			
	Climate Patent Ratio [t]	Number of New Customer Firms			
		Split by Environmental Score		Split by GHG Emissions (Total)	
		High	Low	High	Low
Technology Obsolescence Difference	-0.014***				
(*Instrumental Variable*)	(0.004)				
$\widehat{\textit{Climate Patent Ratio}}$ [t-1]		1.627***	0.341	1.531**	0.309
(*Instrumented by Tech. Obsolescence Diff.*)		(0.619)	(0.751)	(0.600)	(0.785)
Number General Patents [t-1]	0.087***	-0.035	0.001	-0.015	0.004
	(0.005)	(0.029)	(0.022)	(0.022)	(0.019)
Number Existing Customers [t-1]	0.006	0.365***	0.314***	0.224***	0.209***
	(0.005)	(0.026)	(0.016)	(0.025)	(0.021)
Firm Controls	Y	Y	Y	Y	Y
Firm F.E.	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y
Weak Instrument F Test	16.627				
Num. Obs.	6257	5519	5519	5109	5109
Sample	2011 – 2021	2011 – 2021	2011 – 2021	2011 – 2021	2011 – 2021

Panel B: Reduction of CO2 for Customers

Reduced Form 2SLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 1 Emission Total			Scope 2 Emission Total		
Measured in	$t+3$	$t+4$	$t+5$	$t+3$	$t+4$	$t+5$
Supplier's Tech. Obsolescence [t]	3.690**	3.993**	3.779*	4.377*	3.352	0.066
(Climate Innovation)	(1.709)	(1.982)	(2.274)	(2.356)	(2.910)	(4.095)
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.	8704	6525	5170	8698	6514	5154

Internet Appendix for

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

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 filing 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

Panel B: Process and Product Patents by CPC Y02 Categories

Patents by (Filing) Year	Buildings Y02B				ICT Y02D				Energy Y02E				Waste Y02W			
	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 (Filing) Year	Production Y02P				Transportation Y02T				GHG Storage Y02C			
	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.

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) $\times$ 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

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 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 $\times$ 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

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 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 $\times$ 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. Supplier's Climate Patents and Customer's CO2 Emission Changes, by Industry

This table divides the customer sample based on the industry classification of the customer firms. The sample used in the regressions follows Table 2, Panel A. Each observation in the customer sample represents a firm-year observation, where at least one supplier firm sells products or services to the given customer in that specific year. We only include supplier-customer relationships with non-missing sales information. Customer firms in the financial, retail, and wholesale industries are excluded from the sample. Additionally, firms without CO2 emission information from Trucost are also excluded. Total emissions are 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 that sell 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 ratio is calculated as the number of newly invented climate patents 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 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: Customer Firms in Coal Mining, Manufacturing, and Transportation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change in 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 Ratio [t]	-2.361**	-2.248*	-4.756**	-4.163**	-7.313**	-7.260***	-9.646**	-9.039**	-13.081***	-14.062***
	(1.146)	(1.282)	(2.267)	(2.039)	(3.002)	(2.660)	(3.857)	(3.655)	(4.691)	(4.268)
Supplier's General Patent Number [t]	-0.399	-1.354	-0.462	-1.794	-0.086	-1.321	-1.212	-3.424	-0.760	-3.902
	(1.119)	(1.135)	(2.466)	(2.363)	(3.501)	(3.262)	(4.559)	(4.257)	(5.557)	(5.581)
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.	1387	1342	1369	1316	1259	1206	1151	1101	1042	993
Adjusted R^2	0.105	0.083	0.143	0.134	0.142	0.150	0.145	0.219	0.168	0.263

Panel B: Customer Firms in Services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change in 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 Ratio [t]	-1.041	-1.662	-1.695	-2.460	-5.501	-5.148	-3.467	-5.437	-1.215	-3.297
	(1.148)	(1.102)	(1.727)	(1.913)	(4.116)	(5.523)	(5.651)	(6.075)	(6.280)	(8.262)
Supplier's General Patent Number [t]	1.473	3.812*	2.808	7.211*	-0.885	5.942	-5.856	1.483	-9.899	-0.803
	(2.162)	(2.003)	(4.498)	(3.997)	(6.018)	(5.640)	(8.470)	(7.180)	(10.930)	(8.337)
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.	398	382	392	374	344	327	301	282	264	244
Adjusted R^2	0.136	0.057	0.160	0.040	0.194	0.030	0.162	-0.057	0.232	0.030

Table A5. Supplier's Climate Patents and Customer's CO2 Emission Changes, by Different Y02 Patent Categories

This table examines different Y02 categories. In this analysis, the Supplier's Climate Patent Ratio is defined using only one Y02 patent category at a time. The sample used in the regressions follows Table 2, Panel A. Each observation in the customer sample represents a firm-year observation, where at least one supplier firm sells products or services to the given customer in that specific year. We only include supplier-customer relationships with non-missing sales information. Customer firms in the financial, retail, and wholesale industries are excluded from the sample. Additionally, firms without CO2 emission information from Trucost are also excluded. Total emissions are 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 that sell 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 ratio is calculated as the number of newly invented climate patents 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 expenditure, sales growth, and property, plant, and equipment (PPE). All regressions include industry (NAICS 4-digit) $\times$ 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.

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
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 A6. Supplier's Climate Innovation and Customer's CO2 Emissions, The First Year Relationship

This table provides an extension analysis for Table 3 Panel D and E. running regressions using a supplier × customer × year sample. The dependent variable is the customer's future Scope 1 CO2 emissions in year $t+k$. The climate patent number represents the ratio of newly invented climate patents in year t by the supplier in the supplier-customer pair. We add an interaction term between Supplier's Climate Patent Ratio [t] and I(First Year), a dummy equal to 1 if the observation is the first year in which a given supplier and customer firstly establish the supply-chain relation. Standard errors are clustered at the firm level in Panel A to C and at the supplier-customer pair level in Panel D. Statistical significance is denoted by *, **, and ***, indicating significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Supplier-Customer Pair Sample						
	(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]	-4.759***	-4.214***	-4.422***	-4.597***	-4.323***	-4.115***
	(1.270)	(1.508)	(1.529)	(1.219)	(1.445)	(1.396)
I(First Year)	-0.014*	-0.018*	-0.009	-0.014*	-0.018**	-0.015
	(0.008)	(0.009)	(0.011)	(0.007)	(0.009)	(0.011)
Supplier's Climate Patent Ratio [t] x I(First Year)	0.504	-1.063	-2.165**	1.413*	-0.159	-0.639
	(0.777)	(0.945)	(1.051)	(0.749)	(0.937)	(1.047)
Supplier's General Patent Number [t]	1.913	2.421	0.579	2.488	2.581	0.105
	(1.879)	(2.236)	(2.456)	(1.822)	(2.113)	(2.194)
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]	-2.578**	-2.151	-1.584	-2.402**	-2.259	-1.339
	(1.245)	(1.649)	(1.845)	(1.199)	(1.566)	(1.745)
I(First Year)	-0.022**	0.008	0.015	-0.023***	0.006	0.003
	(0.009)	(0.012)	(0.014)	(0.009)	(0.011)	(0.013)
Supplier's Climate Patent Ratio [t] x I(First Year)	0.139	-1.322	-1.607	0.956	-0.312	0.177
	(0.708)	(0.965)	(1.222)	(0.670)	(0.903)	(1.148)
Supplier's General Patent Number [t]	-1.238	-0.593	-1.301	-0.934	-0.578	-2.060
	(1.664)	(2.085)	(2.458)	(1.575)	(1.957)	(2.269)
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 A7. 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)	(2)	(3)	(4)	(5)	(6)
	t+1		t+2		t+3	
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 A8. Robustness Check for Table 6 (Post-2010 Sample Only)

This table provides the robustness checks for Table 6 using only the post-2010 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 $t-1$. 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. 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: Split Customer Firms 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]	0.118***	0.125***	-0.007	0.051	0.066*	-0.009
	(0.035)	(0.031)	(0.025)	(0.047)	(0.040)	(0.035)
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.	22326	22326	22326	22125	22125	22125
Adjusted R^2	0.208	0.139	0.171	0.282	0.208	0.244

Panel B: Split Customer Firms 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]	0.100***	0.089***	0.015	0.039	0.058	-0.015
	(0.035)	(0.031)	(0.022)	(0.048)	(0.043)	(0.030)
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.	21818	21818	21818	21626	21626	21626
Adjusted R^2	0.209	0.152	0.158	0.271	0.208	0.225

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

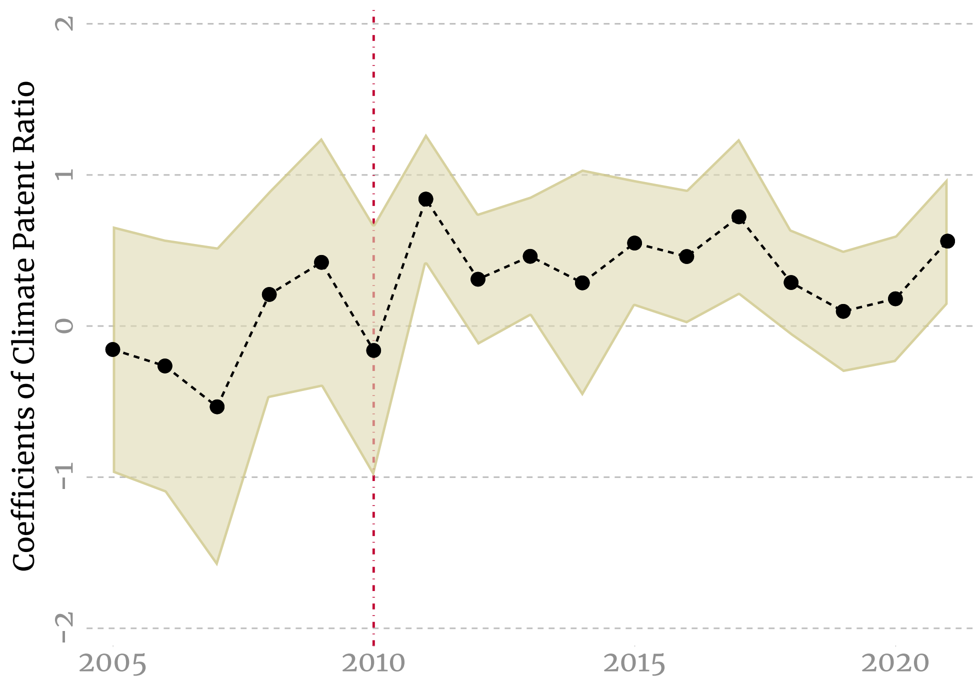
	(1)	(2)	(3)	(4)	(5)	(6)
	Number of New Customer Firms (Attracted by the Supplier)					
Customer Type	All Firms	High Total Emission	Low Total Emission	All Firms	High Total Emission	Low Total Emission
Supplier's ···						
Climate Patent Ratio [t-1]	0.182***	0.197***	0.006	0.045	0.069*	-0.027
	(0.039)	(0.036)	(0.034)	(0.053)	(0.041)	(0.038)
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.	20153	20153	20153	19923	19923	19923
Adjusted R^2	0.272	0.182	0.257	0.368	0.269	0.377

Table A9. Discrete Choice Model Regarding the Selection of Suppliers (Only New Suppliers)

This table estimates a McFadden discrete choice model of selecting potential suppliers by each customer firm. For each customer firm that has at least one supplier in a given year, the set of alternatives includes (i) those suppliers that are selected by the given customer firm and (ii) those suppliers with similar products that the given customer does not select. We use Hoberg and Phillips (2016)'s text-based network industry classification (TNIC) to obtain the second set of suppliers (not selected). 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 equal to one if the customer firm chooses 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 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) d_sc_relation	(2) d_sc_relation	(3) d_sc_relation	(4) d_sc_relation	(5) d_sc_relation	(6) d_sc_relation	(7) d_sc_relation	(8) d_sc_relation
Supplier's Climate Patent Ratio [t-1]	0.016***		0.012***	0.032**	-0.003	0.020		
	(0.003)		(0.003)	(0.015)	(0.004)	(0.015)		
Supplier's Num. General Patent [t-1]	0.001***		0.001***	0.001***	-0.000	0.000		
	(0.000)		(0.000)	(0.000)	(0.001)	(0.001)		
Supplier's Climate Patent Ratio [t-1] × Post 2010		0.019***					0.014***	-0.003
		(0.004)					(0.004)	(0.004)
Supplier's Climate Patent Ratio [t-1] × Before 2010		0.007					0.003	-0.002
		(0.006)					(0.006)	(0.006)
Supplier's Num. General Patent [t-1] × Post 2010		0.001***					0.001***	0.000
		(0.000)					(0.000)	(0.001)
Supplier's Num. General Patent [t-1] × Before 2010		0.001*					0.001	-0.002***
		(0.000)					(0.000)	(0.001)
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t]			0.009***	0.018***	0.006*	0.017***		
			(0.003)	(0.006)	(0.003)	(0.005)		
Supplier's Num. General Patent [t-1] × Customer's Environmental Score [t]			-0.001***	-0.001***	-0.001***	-0.001***		
			(0.000)	(0.000)	(0.000)	(0.000)		
Supplier's Climate Patent Ratio [t-1] × Customer's Social Score [t]				-0.010*		-0.014***		
				(0.006)		(0.005)		
Supplier's Climate Patent Ratio [t-1] × Customer's Governance Score [t]				-0.002		-0.000		
				(0.004)		(0.003)		
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t] × Post 2010							0.010***	0.007*
							(0.004)	(0.004)
Supplier's Climate Patent Ratio [t-1] × Customer's Environmental Score [t] × Before 2010							0.008	0.005
							(0.005)	(0.005)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Customer Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Supplier's Industry F.E.	Y	Y	Y	Y			Y	
Supplier's Firm F.E.					Y	Y		Y
N	647244	647244	647244	637968	647053	637778	647244	647053
Adjusted R^2	0.044	0.044	0.044	0.044	0.159	0.160	0.044	0.159

Figure A1. Supplier's Climate Patent Ratio and Number of 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:

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t \Big) + \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (15)$$

Where $Num\_New\_Customer\_Firms_{i,t}$ signifies the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. We conduct Poisson regressions 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 invented by the firm to all patents invented by the same firm in year $t-1$. The regression model encompasses 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.