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“Climate Innovation and Carbon Emissions: Evidence from Supply Chain Networks”

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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 then look at the diffusion of climate innovation to new customers. We find that customers exhibit a strong preference for suppliers with new climate patents, that climate patents allow suppliers to attract new customers, especially customers with high environmental ratings or a large carbon footprint, and that these new customers subsequently also reduce their emissions. We use the quasi-random assignment of patent examiners and the exogenous technological obsolescence of climate patents as instruments to suggest a causal interpretation of the main findings.

Key words: climate innovation; supply chains; new customer firms; business stealing; carbon emissions; environmental scores; patent examiner leniency; technology obsolescence.
JEL classification: L14, O31, O33, Q54, Q55.

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1 Introduction

It is widely assumed that climate innovation will play a central role in the global transition to climate neutrality. 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 currently 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 the pursuit of the Paris Agreement goals of 2015 (IPCC, 2022).

The incentives to develop new climate technologies are encumbered by two fundamental market failures: social benefits typically exceed the private return for innovators and existing policies such as carbon taxes or regulations internalize global climate externalities at best imperfectly.[1] In spite of these obstacles, there is a significant 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.[2] 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 innovators' carbon emissions, neither for renewables or clean energy (green patents) nor for fossil energy efficiency (brown patents), and regardless of the horizon considered. Bolton et al. (2023) attribute this finding to a rebound effect or Jevons paradox (Jevons, 1865), the idea that fossil energy savings may simply induce a larger demand for energy. 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.[3]

Many climate patents, however, are product innovations and hence the emission benefits should

[1]The first issue is prominent in the economics of innovation literature (see Arrow, 1962; Griliches, 1992; Hall, Mairesse, and Mohnen, 2010, for a survey), the second is also present for other environmental externalities, see e.g. Gillingham, Newell, and Palmer (2009).

[2]Starting in 2010 after an appeal of the UNFCCC (UN 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 that we use in our paper. 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).

[3]They also find no effect on innovators' Scope 3 emissions and neither do we, as we discuss in Section 3.2.

accrue at the customers that use the innovator's products. Looking at the innovating firm then misses the place where emission savings are expected to occur. This is a relevant concern: we show that 70% of US climate patents are product innovations, hence their principal emission benefit should not accrue at the innovators or their peers.

Many countries, including the US, Europe and China, have put in place myriads of public policy schemes to foster climate innovation, such as subsidies on the supply and demand side. Finding direct, micro-level evidence in favor of emission benefits of climate innovation is therefore relevant for the evaluation of such public policies. In this study, we examine how a supplier firm's climate innovation affects the CO2 emissions of its customer firms. Since we are motivated by the question whether climate innovation contributes to GHG emission reductions, we consider not only the impact on existing customers within current supply chain networks (*intensive margin* channel) but also the question whether climate innovators are able to acquire new customer firms that subsequently succeed in reducing GHG emissions as well (*extensive margin* channel). We argue that adding the extensive margin channel is essential to get a broad view of the knowledge diffusion and the emission benefits of climate patents. In a nutshell, we find strong evidence that climate innovation reduces carbon emissions both through the intensive and the extensive margin channel.

First, we explore the intensive margin – the impact on existing supply chain networks. To analyze the emission impact in supply chain networks, we identify important customers using the FactSet Revere supply chain and the Compustat customer segment database, widely used in research on supply chains and construct a supplier × customer × year sample by merging these data with data on patents, firm and product characteristics, and carbon emission data. Using panel regressions, we find that more climate patents of suppliers lead to subsequent reductions in CO2 emissions of customers. We find this effect consistently for Scope 1 (direct) and Scope 2 (indirect) emissions, and for total emissions (tons of CO2) as well as for emission intensities (total emissions divided by firm output).[4] Since our focus is on product innovations, we identify product patents following Bena, Ortiz-Molina, and Simintzi (2022). We find that almost 70% of climate patents are product innovations, and show that the emission effect is essentially driven by product patents; when we apply the same analysis to climate patents granted for process innovations, we find very weak effects.

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

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, that is concerns that firms aiming to reduce emissions might opt for climate innovators as suppliers (to analyze a causal link between climate patents and customer emissions, we later use two instruments as exogenous shocks to the climate patenting and innovation capacity).

Next, we turn to the extensive margin of the emission benefits of climate innovation – GHG emission reductions of newly acquired customers. We first investigate whether climate innovations help suppliers to expand their business and attract new customers, and we identify the types of customers it attracts. This is an essential question to understand whether climate technology is indeed widely adopted (Hall and Helmers, 2010), as assumed e.g. in the IEA (2021) scenarios, which is crucial in light of the global public benefits of the rapid diffusion of new climate technology. "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.[5]

To test this hypothesis, we first try to understand customers' preferences for suppliers featuring climate innovation. We construct an empirical discrete choice model (McFadden, 1974) regarding the selection of potential suppliers by customer firms.[6] For each customer firm that has at least

[5]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.

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

one supplier 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 determine 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 a supplier. Moreover, we observe that this preference is stronger for customer firms with higher environmental scores or higher initial carbon emissions. To further validate our findings, in an alternative specification we consider solely the choices of new suppliers. This analysis strengthens the case that customers actively make choices and that the observed effect is not only explained by continued supply chain relationships.

Next, we examine 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 effect is not significantly different from zero prior to 2010. While we are not able to pinpoint a specific cause for the absence of significant effects prior to 2010, we note that the literature documents a structural break in the public attention to climate change around that time, typically attributed to the failure of the COP15 meeting in Copenhagen 2009[7] and other concurrent developments (Ardia, Bluteau, Boudt, and Inghelbrecht, 2022), and visible in a widening valuation gap between high-emission and low-emission firms around 2010 (Choi, Gao, Jiang, and Zhang, 2022). The year 2010 also coincides with the creation of the "Y02/Y04S" tagging scheme (EPO, 2015) and concomitant initiatives to enhance the impact and visibility of climate patents, notably the USPTO Green Technology Pilot Program. Consistent with the notion of a structural break in 2010, we show in event studies following Kogan, Papanikolaou, Seru, and Stoffman (2017) a positive jump in the value of climate patents after 2010, with no comparable effect in the value of

However, 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.

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

general patents.

We then investigate transmission channels for the capacity to attract new customers. We expect that firms with high environmental ratings or high emissions should have a higher willingness-to-pay for climate-innovative products.[8] We find that new 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.

After documenting the "business stealing" effect of climate innovation, we examine its impact on emission reduction for new versus existing customers. Our results show that new customers reduce Scope 1 emissions by 11% over five years, compared to 4% to 5% for existing customers. We further find that the emission impact is stronger for high-emission customers and in the most emission-sensitive technology categories (energy, transportation, and 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 customer's main sector belongs to resource extraction (mining, oil and gas), manufacturing, or transportation.

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

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

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. We introduce two instrumental variables to address such omitted variable concerns. Our first instrument 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 (Cockburn, Kortum, and Stern, 2002; Sampat and Williams, 2019). We follow the literature that the patent examiner 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 located at the climate technology frontier and that the aging of an innovator's knowledge base is determined by technology advances of other firms, and hence exogenous for the innovator under consideration. Using these two instrumental variables in 2SLS regressions, we corroborate our main findings on the intensive and extensive margin impact of climate patents.

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

Second, our paper is closely related to recent work on climate change concerns and the supply chain. Schiller (2018) and Dai, Liang, and Ng (2021b) show that ESG policies of customer firms can propagate to supplier firms, but not vice versa. HomRoy and Rauf (2023) show that supply chain connections influence the adoption of climate-responsible policies. More specifically, Deng, Duan, Li, and Pu (2023) show that major corporate customers induce significant reductions in their suppliers' carbon emissions, in particular when they have emission-reduction commitments, face higher climate regulatory risk, and have lower switching costs and stronger bargaining power. 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. On the other hand, Dai, Duan, Liang, and Ng (2021a) provide evidence that firms outsource part of their carbon emissions to foreign suppliers. We contribute to this literature by demonstrating the real emission impact of climate-related technologies in supply chains, by showing that climate patents also create new supply chain links and are effective in existing and supply chains, and by widening the perspective from the focus on customer motives by showing that suppliers expand their customer base and sales.

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

The paper is organized as follows. We explain our data strategy and main variables and provide summary statistics in Section 2. Section 3 presents the first part of our analysis, on the link between supplier climate patents and GHG emissions at customer firms. Section 4 contains the second part, knowledge diffusion of climate patents via the acquisition of new customers. Section 5 addresses endogeneity concerns and presents two distinct identification strategies. The final section concludes.

2 Data and Sample Construction

2.1 Sample of Climate Patents

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

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

[10]Our extension to patents granted in 2022 and 2023 aims to partially mitigate the well-known patent truncation bias described in Lerner and Seru (2021), which is particularly important for climate patents given their recent nature. 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.

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 process patent if its first claim (usually the most important claim) begins with the words "a process of," "a method of/for," and so on. Close to 31% of climate patents are process patents. Table A1 further tabulates the annual number of climate patents by "Y02" categories. Y02E (Energy) and Y02T (Transportation) are the two largest categories, accounting for nearly 60% of total climate innovation, and product innovation clearly dominates in these categories (as shown in Table A1 Panel B).

For our extensions and our instrumental variables, 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

[11] We exclude patents with the Y02A and Y04S tags, the patent tags 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.

[13] For details about this dataset, see Graham, Marco, and Miller (2018).

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 customers have ESG ratings recorded in at least one of the three ESG databases (Refinitiv, Sustainalytics, and S&P Global), this number drops to 48,563. Furthermore, 43% of the relationships last fewer than three years. Panel B reports data for the subsample that contains sales information for the supplier-to-customer sales. This is a much smaller subsample, consisting of only approximately 12% of the supplier-customer relationships in the full sample, and it largely coincides with the data obtained from 10-K filings where sales reporting is mandatory. This subsample is used in our baseline regression since it allows for the most accurate measurement of the variable of interest.

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

2.3 CO2 Emissions and Environmental Ratings Data

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

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

company. We only use Scope 1 and Scope 2 emissions in our main analysis and exclude Scope 3 emissions.[15]

Furthermore, to investigate which types of business customers are attracted by climate innovation, we obtain environmental ratings for customer firms from three ESG ratings data providers: LSEG ESG (formerly Refinitiv ESG, and originally Asset4), Sustainalytics, and S&P Global ESG rating. Following Brandon, Glossner, Krueger, Matos, and Steffen (2020), we create a composite environmental score based on these three distinct environmental evaluations in order to maximize the sample coverage.[16]

2.4 Summary Statistics

In our analysis of customer emissions in Section 3, we focus on the 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 firm reports CO2 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.[17]

As shown in Table 2, Panel A, our sample of customers is relatively small (2,831 observations) as we impose quite restrictive sample filters: sales between suppliers and customers must be reported, i.e. supply chain relationships without sales are dropped. This filter is important to obtain the most accurate estimate of our main variable of interest, the sales-weighted average climate innovation of all suppliers of a customer firm, considering that on average, each customer has 4.7 suppliers in a

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

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

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

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

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

given year.[18] 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 contribute little to climate innovation. In the subsample in which we require that suppliers file at least one general patent (the denominator is non-zero), the mean of the climate patent ratio increases to 6%. In this sub-sample, the average number of general patents for suppliers is 11.20, while the average number of climate patents is 0.64.[19] Finally, the annual average (median) Scope 1 CO2 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 and 2.52 existing customers in a fiscal year (the table records logs).

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 existing 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 should be the customers who buy products incorporating new climate technology, the innovating firms themselves. This idea is relevant in light of our finding in Table A1 that almost 70% of US climate patents are granted for product innovations. It is important to recognize that our analysis

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

[19]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.

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 should often be larger than what our study captures.

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

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

where the dependent variable $\Delta_{t,t+k} = \ln(\text{Emissions}_{i,t+k}) - \ln(\text{Emissions}_{i,t})$ measures the forward-looking change in GHG emissions for customer firm i from year t to $t+k$. We use four distinct measures for customer emissions, by distinguishing between Scope 1 (direct) and Scope 2 (indirect, energy-related) emissions and by calculating total emissions (tons of CO2) and emission intensity (emissions divided by firm output) according to Bolton and Kacperczyk (2021a, 2022).[20]

We follow Bolton et al. (2023) and use the climate patent ratio to measure suppliers' climate innovation efforts, as the ratio captures the relative effort of climate innovation in the firm's total R&D output. As in Bolton et al. (2023), our main independent variable, supplier's climate patent ratio,[21] 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.[22] 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. In addition, notably to account for decarbonization trends at the industry level, we introduce industry-year fixed effects. We do not include firm fixed effects since our dependent variable is already differenced. Standard

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

[21] Bolton et al. (2023) argue that patenting activity in any given year is significantly driven by a firm's innovation capacity. Accordingly, new patent filings must be related to the firm's total innovation capacity to get a more accurate picture of the intensive margin of climate innovation activity.

[22] We use the application year of patents, as it better captures the date when innovators start to be in a position to incorporate technologies into products, compared to the patent granting date. Whether the technology is granted or not does not influence the innovator's ability to embed it in their products.

errors are clustered at the customer-firm level.

Table 3 presents our first main result. In Panel A, we consider Scope 1 emissions. We standardize the supplier's climate patent ratio so that it has a standard deviation of 1 and multiply the coefficients by 100 for readability. As shown in Panel A, a one-standard deviation increase in the supplier's climate patent ratio corresponds to a reduction of roughly 10.7% in total emissions (Scope 1) and 12.5% in emission intensity (Scope 1). Interestingly, the effect increases monotonically over the subsequent five years. After five years, the effect translates into a decrease of 47,813 tonnes per year (446,858 $\times$ 10.7%) of CO2 and 6.19 tonnes per million dollars output (49.55 $\times$ 12.5%), respectively.

In Panel B, we look at Scope 2 emissions. We note that the hypothesis regarding changes in Scope 2 emissions is much less clear cut, due to substitution effects. For instance, if climate innovation induces electrification, such as the replacement of vehicle fleets with electric cars, customers' Scope 1 emissions could decrease while their Scope 2 emissions increase. Nonetheless, our findings in Panel B closely match those for Scope 1 emissions. A one-standard deviation increase in the supplier's climate patent ratio is linked 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. Moreover, the coefficients of the Customer's Climate Patent Ratio are all insignificant, indicating that the customer's climate technology has no impact on its own carbon emissions, confirming Bolton et al. (2023).

We find similar results when using the number of climate patents instead of the climate patent ratio, as shown in Table A3 in the Online Appendix. In addition, when we use the past three years' patent stock of suppliers to construct the climate patent ratio, we find similar outcomes, presented in Table A4. One particular concern is that suppliers with high climate patent ratios might be small innovators (for instance, if a firm has only one patent and that patent is climate-related, the climate patent ratio is 1). However, this concern does not appear to be important in our data: when we restrict our sample to firms with a climate patent ratio greater than 0.10, we observe that these firms filed an average of 19.12 climate patents. 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 customer firms. Table A5 in the Online Appendix shows that the impact of climate technology on Scope 1 emission reductions is strongly significant in mining, oil and gas, and utilities (NAICS: 21 and 22), manufacturing (31, 32 and 33) and transportation (48 and 49). In contrast, there are no significant effects in service sectors. This outcome is unsurprising, considering that mining, oil and gas, utilities, manufacturing and transportation are the sectors with the highest direct CO2 emissions.

Finally, we examine the differences between technology sectors, using the Y02 subcategories. As documented in Table A6, climate patents in renewable energy and energy efficiency (Y02E), building technology (Y02B), and transportation (Y02T) exhibit the strongest impact, again progressively growing over a five-year time frame. These three patent categories encompass activities with disproportionately high carbon emissions but also substantial climate patenting activity. This outcome is in line with our finding that emission reductions are more pronounced for firms with high emission intensity (see the discussion of Table 4 below) and with the expectation that these sectors hold the greatest potential for accelerated decarbonization (IEA, 2021). In contrast, we observe a comparatively weaker and less consistent impact of information and communication technologies (Y02D), even though climate patenting activity there is elevated. For carbon capture and storage (CCS, Y02C), caution is warranted when interpreting the results since the patent sample is notably small and concentrated. Finally, and somewhat unexpectedly, our analysis reveals no discernible effect on customer emission reductions concerning the production processes of goods (Y02P).

3.2 Extensions

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

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

In Panel C of Table 4, we distinguish between climate product patents and climate process patents. 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 a stronger effect of process patents compared with product patents on innovator emissions.)

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

There are obviously endogeneity issues, and specifically concerns about selection effects between customers and suppliers. For example, it is possible that firms with a more ambitious climate agenda are more likely to select green suppliers with a more pronounced climate innovation effort. We might then observe a misleading association due to simultaneity bias, even if the supplier's climate patents make no direct causal contribution to the customer's CO2 reduction.

To address this concern, we investigate the change in emissions in a panel of *stable* supplier-customer relationships that exist prior to the application for climate patents. We use a supplier $\times$ customer $\times$ year sample where each observation represents a supplier selling products or services to a given customer in a specific year (t).[23] We include supply chain relationships with both missing and non-missing sales in this analysis.

The regression results, presented in Panel A of Table 5, use the customer's forward-looking Scope 1 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 show that for stable supplier-customer pairs, the customers' CO2 emissions respond to suppliers' newly granted climate patents. The coefficients (standardized and multiplied by 100 for readability) in Panel A 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 B of 5.

It is possible that customers reduce their carbon footprint and engage in parallel efforts to prompt their suppliers to undertake climate innovation. Note that this possibility does not refute our premise that climate patents contribute causally to customer CO2 emission reductions since our premise does not require to identify whether the work on climate patents is primarily initiated by suppliers or by customers (trying to do so would be a daunting task). However, the approach of looking at panel of stable supplier-customer pairs is certainly insufficient to address all possible endogeneity concerns. We show later that climate innovators are able to acquire new corporate customers that subsequently reduce carbon emissions, which may also partially attenuate concerns that customers might reduce carbon emissions independently of their suppliers' climate innovation. Importantly, in Section 5, we use two instruments to introduce exogenous shocks to the supplier's climate innovation and patenting activity, based on random assignments of patent reviewers and technological obsolescence of climate know-how, to address endogeneity concerns.

Finally, in theory, it should be possible to measure customer emissions by the downstream Scope 3 emissions reported by the supplier firm. Scope 3 emissions contain all indirect emissions (not included in Scope 2) that occur in the value chain of the reporting company, including both upstream and downstream emissions. Thus, we extend the analysis and look at innovators' downstream

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

Scope 3 emissions in Table A8. We find no significant effect of climate patents related to product innovations. This finding confirms the result of Bolton et al. (2023) who also look at downstream Scope 3 emissions of innovators in their sample and find no effect. One possible reason is that Scope 3 emission data are unreliable since they are strongly downwards biased: for example, Klaaßen and Stoll (2021) find that reported Scope 3 data in the tech sector omit half of actual Scope 3 emissions.

4 Climate Patents and New Customers

Following our analysis of the "intensive margin" (existing supplier-customer relationships), we turn to the relationship between climate innovation and knowledge diffusion at the "extensive margin", the question whether climate innovation leads to the acquisition of new customers and can help to reduce their CO2 emissions. The "extensive margin" investigates how innovation contributes to the dynamics of supply chain networks which is particularly important in our context in view of the global common goods nature of climate technology.

In fact, it is not a foregone conclusion that climate innovation will facilitate business expansion and the acquisition of new customers, or "business stealing." Suppliers are likely to charge a premium for their climate innovation. Fowlie (2010) documents that reducing GHG emissions is costly and therefore not obviously profit-enhancing. As a result, demand may be stifled. However, the literature provides a number of possible explanations why the net effect may result in business stealing. First, as climate change garners more attention, there is an increase in 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, resulting in a lower cost of capital for firms with lower transition risk (Chava, 2014; Bolton and Kacperczyk, 2022; Pástor, Stambaugh, and Taylor, 2022). Thus, potential new customers should increasingly be receptive to adopt new climate technology and be willing to pay a premium for it.

We tackle the question of "business stealing" in three different explorations. We first examine the customers' perspective regarding their choice of potential suppliers, then turn to the suppliers' perspective and analyze their capacity for business expansion by adding new customers, and finally investigate whether these new customers are able to reduce their CO2 emissions.

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. We investigate the role of climate innovation in this choice to explore whether a typical customer prefers suppliers with more climate innovation.[24]

For each customer firm with at least one supplier in a given year, we create a choice set of possible suppliers. We first include the suppliers that are actually chosen. We then identify potential 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,

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

where the dependent variable $I(\text{Select})_{c,s,t}$ is a dummy that equals one if the customer firm c selects the supplier s to establish the supply chain relationship in year t. 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 discrete choice model in two important ways. First, a textbook 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).

Table 6 reports the findings. In column (1), the coefficient of the supplier's climate patent ratio is positive and highly significant, implying that customers prefer suppliers with climate innovations. Specifically, an increase in the interquartile range of the climate patent ratio is associated with a 12% increase in the probability of selecting that supplier. The effect is also strongly positive for

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

general patents. This is a necessary control variable in our context to make sure that climate patents are not simply picking up a reaction to general supplier innovation, and the strongly significant and positive coefficient also underlines the validity of our methodology.

To the best of our knowledge, this empirical approach is novel in the innovation and in the supply chain literature and we are the first to document such a business expansion effect (acquisition of new customers) for supplier patents in general (an analysis of dynamic supply chain reactions to innovation is absent in the literature).

Column (2) of Table 6 breaks the sample period into two sub-periods, before and after 2010. The regression reveals that the effect, while seemingly significant for the full sample, is really explained only by climate patents with application date starting in 2010: only the coefficient on the supplier's *climate patent ratio* $\times I$(Post 2010) is positive and significant, i.e. customer firms start to express a positive preference for climate innovation only after 2010. In contrast, there is no significant difference between the coefficients of supplier's *number of general patents* $\times I$(Post 2010) and supplier's *number of general patents* $\times I$(Before 2010). This means that there is a structural break around 2010, and that this break only matters for climate patents. We discuss this structural break in the next section, after providing 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 6 shows in column (3) that the interaction term between the supplier's climate patent ratio and the customer's environmental score (E-score) is positive and significant, indicating that customer firms with a high environmental score have a stronger preference for the supplier's climate technology. In contrast, the interaction term between the supplier's number of non-climate patents and the customer's E-score is insignificant. Column (4) conducts placebo tests by adding the interaction terms between the climate patent ratio and the social score and governance score (the other subscores in their ESG score). It shows that the stronger preference is not true for customers with high governance or social scores. Column (5) interacts with a post-2010 dummy and shows that the preference for suppliers with new climate technology by customers with a high E-score exists only after 2010, as shown by the triple interaction term (interacting with I(Post 2010) and I(Before 2010), respectively). By contrast, including customer size does not alter the results (column (6)). A high environmental score is considered as a proxy for firms' preferences regarding environmental and climate change issues,[25] implying a greater willingness-to-pay for climate innovation.[26]

In columns (7) and (8) of Table 6, customers with high emissions (either measured by total emissions or by emission intensity) are more likely to choose climate-innovative suppliers.[27] Again, this supplier-customer combination is more frequent after 2010, but not before 2010. At first sight, it may appear paradoxical that high-emission firms exhibit a stronger propensity to select suppliers with climate technology advances. To understand this finding, we note that, first, high-emission firms are not necessarily those with low environmental scores. Table 2, Panel D, shows a very low pairwise correlation between the components of the environmental score and CO2 emissions.[28] Second, customer firms with large carbon footprints have reasons to be sensitive to climate innovation because of the potential larger benefits of reducing emissions: high-emission firms tend to be exposed to the strongest pressure from climate-conscious institutional investors (Atta-Darkua et al., 2022) and to have a higher cost of capital (Bolton and Kacperczyk, 2021b), providing an additional financial motive for major carbon emitters to cut their emissions. Finally, our findings are in line with the evidence of Cohen et al. (2021) that high-emission firms are also active climate innovators themselves.

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 suppliers' perspective and their capacity to attract new customers. We construct our sample of potential suppliers following Section 2.4 and then run the following regres-

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

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

[27]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.

[28]To understand the low correlation, similar to findings e.g. in Boffo, Marshall, and Patalano (2020), it is useful to recall that environmental scores are calculated relative to each industry, while CO2 emissions are measured in absolute terms; also, environmental scores typically encompass many more dimensions than GHG emissions.

sion,

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

The dependent variable "Num_New_Customer_Firms" counts how many *new business customers* start to purchase products or services from firm i in year t.[29] From now on, we calculate the climate patent ratio using the patent granting year, as the granting date better reveals a signaling effect. We lag the climate patent ratio by one year and interact it with $\Big\{I(\text{Year})_t\Big\}_{\text{Year}=2005}^{2021}$, a set of dummies equal to 1 in year t, where $t = 2005, 2006, \cdots, 2021$. The interaction helps to study the possibly time-varying effect of climate innovation on the acquisition of new customers. Moreover, we control the number of general patents measured in year t-1.[30] We plot the coefficients of $\beta_{1,\text{Year}}$ as well as their confidence intervals at the 90% level in Figure 1.

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% to 22.06% increase in the number of new business customers. In contrast, the coefficients before 2010 are not significantly different from zero. In the Online Appendix (Figure A1), we conduct robustness checks using Poisson regression and find similar results.[31] In Figure A2, calculating the climate patent ratio using the patent application date yields results similar to those based on the granting date, but with greater fluctuations in the coefficients post-2010.

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

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

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

4.3 Customer Acquisition and the Structural Break Around 2010

Although we find a strong structural break in 2010 in our regression analyses, we cannot pinpoint the causes because there are several concomitant developments around 2010. First, the failure of the December 2009 Conference of the Parties (COP15) to produce a new global climate agreement had the effect of a shock that significantly raised public attention to climate change (Ardia et al., 2022). In line with this idea, papers on the market reactions to climate news typically find a similar structural break during 2010 and 2011. For example, Choi et al. (2022) show that the price valuation gap between high-emission firms and low-emission firms was close to zero before 2011 but significantly negative afterwards. Second, the break is possibly related to the introduction of the "Y02/Y04S" scheme by the European Patent Office (EPO) and the USPTO which allowed to easily identify whether a given patent is climate-related. Previously, 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). Third, there were other simultaneous initiatives to enhance the impact and visibility of climate patents. 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. These schemes, including the "Y02" scheme, helped stakeholders including customer firms to quickly screen for climate-relevant patents and they could also be exploited in the marketing efforts of innovating firms.

To further examine the 2010 structural break, we plot the annual median market value of climate and non-climate patents separately in Figure 2.[32] 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.[33] For climate patents, we only include Y02E (renewable energy and energy efficiency) and Y02C (carbon capture and storage) because the original Y02 scheme in 2010 only included these two categories (Veefkind, Hurtado-Albir, Angelucci, Karachalios, and Thumm, 2012; Calel, 2020). The figure shows a large jump between 2010 and 2011 in the value of climate patents. By contrast,

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

a similar jump does not exist for non-climate patents. This implies that after 2010, climate patents are able to attract not only the attention of customers but also of financial markets. Interestingly, we don't find a similar 2010 jump for other Y02 categories that did not exist in 2010 and that were only backfilled several years later, showing that the relatively prompt delivery of the "Y02" tag was probably important.

Next, we explore the heterogeneity of new customers from the innovator's perspective, asking what types of customer firms it can most likely attract after climate patent grants. Table 7 addresses this question by estimating the following regression,

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

In columns (1) and (4) in Panel A of Table 7, the dependent variable is 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 the sample of all new customers in a given year using their environmental scores (see Section 2.3). In columns (2) and (5) ((3) and (6)), the dependent variable counts only those newly acquired customers with environmental scores above (below) the sample median of that year. 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 corroborate the findings presented in Figure 1, demonstrating that climate innovation has been instrumental in attracting new business customers post-2010, but not prior to that year. Additionally, in columns (2) and (5), the regression coefficients for the number of new customer firms with high environmental scores are positive and significant. This finding indicates that climate technology is particularly effective in attracting new customers prioritizing environmental performance, in line with our earlier findings from the discrete choice model presented in Table 6, column (3).

In Panel B of Table 7, we conduct a similar sample split, using a measure of customer's active environmental engagement in their supply chain management. The variable used for the median split, constructed by LSEG (formerly Refinitiv), indicates whether a customer firm considers environmental impacts when selecting its suppliers.[34] As illustrated by the coefficients in Panel B, a supplier's climate innovation significantly attracts new customer firms committed to environmental supply chain management, but this effect is observed only after 2010.

In Panel C of Table 7, we undertake another sample split based on the annual CO2 emissions of customers, using the sum of Scope 1 and Scope 2 emissions (in tons). We do not make any within-industry adjustments for CO2 emissions, following Bolton and Kacperczyk (2022)'s perspective that raw and total carbon emissions more accurately capture a firm's carbon transition risk. Similarly, Choi et al. (2022) use industry-level emissions measures in their analyses. Echoing our findings in Table 6, we find in Panel C that new customers attracted by a supplier's climate technology are those with high CO2 emissions. Conversely, firms with relatively low emissions are less likely to purchase products from climate innovation suppliers, as indicated by the negative coefficients of the climate patent ratio $\times I(\text{Post } 2010)$ in columns (3) and (6).

Finally, we investigate whether the acquisition of new customers after 2010 is not just a consequence of increased customer turnover following climate innovation. To do so, we consider the choices of climate innovators' existing customers, and specifically whether they remain loyal or switch to other suppliers, possibly as a result of higher costs or unwanted changes in technology. In Panel D of Table 2, we regress the number of existing customers who stop buying products from a given climate innovator, before and after 2010. It shows that existing customers do not tend to defect from climate innovators, as all coefficients in the three columns are far from significant. In summary, climate innovations help suppliers attract new customers, but do not drive away old customers. They appear to benefit from a net gain in their customer base.

4.4 Customer Firm's Carbon Emissions: New and Old Suppliers

In our third and final pass, we turn to the question whether climate innovation helps new business customers to cut emissions and how the magnitude of the reduction compare to that of existing customers.

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

Table 8 analyzes the relationship between changes in future carbon emissions for customer firms and the role of new and long-standing suppliers with climate patents. The analysis uses two dummy variables: "I[New Supplier with Climate Patents]," which is equal to 1 if the firm has a new supplier with a climate patent ratio greater than 0.2, and "I[Old Supplier with Climate Patents]," which is equal to 1 if the firm has long-standing suppliers (relationships starting five years ago) with a climate patent ratio greater than 0.2.[35] The climate patent ratio is calculated using the supplier's patents with applications filed in years $t-2$, $t-1$, and t. Panels A and B present the results for Scope 1 and Scope 2 emissions, respectively. Panel A shows that the reduction impact for firms with a new supplier is approximately 11% after five years. Thus, the measured emission reduction impact is significantly larger than for customer firms with climate innovation in existing supply chain relationships, where we observe a reduction of 2% to 5%. Qualitatively, our findings for new customers align with our earlier results for existing customers on the role of high-emission firms: (i) most new customers are high-emission firms (Table 7, Panel C), and (ii) climate technology has the most substantial impact on high-emission firms (Table 4, Panel B). Similar results are observed for Scope 2 emissions.

In summary, climate innovation is effective in reducing CO2 emissions for both new and existing customers, with a more pronounced effect observed in new customers, particularly in terms of direct emissions. This reflects the strategic alignment of high-emission firms with climate technologies to meet regulatory demands and corporate sustainability objectives, underscoring the critical role of innovative suppliers in facilitating substantial environmental impacts.

4.5 Operating Performance of Climate Innovators

We have shown that climate innovation helps suppliers to attract new customers, but does not lead to the departure of existing customers (Table 7). The resulting net gain in customers, as well as possible larger sales or profits because climate-innovative products may command a higher mark-up, can be expected to ultimately lead to sales growth and profit improvements. To explore this idea, Table 9 examines how climate innovation affects suppliers' operating performance. In column (1) of Table 9, the dependent variable is the natural logarithm of sales. Consistent with our intuition, the coefficient of the climate patent ratio (t-1) $\times I$(Post 2010) is positive and significant. Climate

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

innovation is associated with sales growth, but only after 2010. In columns (2) and (3), we examine return on assets (ROA) and mark-ups, respectively, where the variable mark-up is defined as (total sales − cost of goods sold)/(total sales). Interestingly, the climate patent ratio (t-1) $\times I$(Post 2010) is positive (but not significant), but the coefficients of the climate patent ratio (t-1) $\times$Before 2010 are both negative and significant. Thus, there is indeed a significant improvement in sales and mark-up after 2010, but the initial effect of climate patents on return on assets and mark-ups of innovators is negative (the latter result is consistent with the findings by Bolton et al. (2023) that the climate patent ratio predicts declining market shares and profits). Our suggested interpretation is that prior to 2010, when the willingness-to-pay for climate mitigation was low, climate innovators were probably not able to pass on the cost of their innovation activity in form of higher mark-ups, and their profitability deteriorated. After the structural break around 2010 (Section 4.3), they managed to obtain an adequate return on their climate innovation investment.

4.6 New Customers, Patent Quality, and Product Relatedness

In this section, we look for corroborating evidence by asking whether more valuable climate patents have a stronger pull effect in attracting new customers. We explore the heterogeneous impact by differentiating climate patents according to various measures of their usefulness. First, we differentiate climate innovations by patent quality (see Cohen (2010)). Patent citations, the traditional measure of patent quality (Jaffe and Trajtenberg, 2002), are problematic in the context of climate patents that are overwhelmingly fairly recent, in view of the long lag in patent citations (Lerner and Seru, 2021). Therefore, we use Kogan et al. (2017)'s measure of the market value of patents as proxy for patent quality.[36] In Panel A of Table 10, we split our climate patent ratio into two subcategories, with Climate Patent Ratio (High Value) counting the number of new climate patents (filed by firm i in year t and ultimately granted) with a market value above the median of all climate patents in year t (and Climate Patent Ratio (Low Value) those below the median). The dependent variable in Table 10 is the number of new customers acquired by a given supplier. We distinguish new customers along the two dimensions considered before, high/low environmental score and high/low carbon emissions. The coefficients in Panel A of Table 10 show that the capacity

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

of climate innovators to attract new customers is clearly driven by high-value climate patents.

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

We use an advanced deep-learning method in natural language processing to compute the pairwise document similarity between a given patent text and the patent holder's product description. A higher similarity (technically, cosine similarity) is interpreted as implying that a given patent is more critical for the firm's core products. To obtain patent content, we follow Kogan et al. (2021) by using the title, abstract, and detailed description text of the patent. We obtain product descriptions from 10-K filings (Item 1. Business Description) following Hoberg and Phillips (2016). We then use the Stanford GloVe model (Global Vectors for Word Representation) to compute pairwise text similarity between climate patent text and product description text.[37] Figure 3 shows and discusses an example of our pairwise document similarity, for a patent granted to Western Digital with the Y02D tag.

Panel B of Table 10 reports our results. It shows that only climate patents that are highly correlated with the supplier's products attract new customers. The dependent variable is still the number of new customers acquired by a given supplier. We distinguish new customers along two dimensions: Environmental score and GHG emissions (Scope 1). We sort all climate patents into two groups by the median of product-patent cosine similarity. Climate Patent Ratio (Highly-Related) is equal to the number of new climate patents (filed by firm i in year t and ultimately granted) whose product-patent cosine similarity is higher than the annual median cosine similarity for all climate patents divided by the total number of general new patents filed by firm i in year t.

[37] 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).

Panel C shows that new customers are primarily acquired in times of high public attention to climate change, indicated by the interaction of Climate Patent Ratio with the MCCC-index, a widely used index of the news coverage of climate change. This also highlights the importance of patent value since, as Ardia et al. (2022) show, the MCCC index is strongly correlated with the appreciation of corporate climate policies.

5 Endogeneity: Instrumental Variables Approach

Our analysis has unveiled two key findings: first, climate innovators significantly help customers in cutting CO2 emissions. Second, customer firms exhibit a significant propensity to choose suppliers engaged in climate innovation and to subsequently cut their emissions. Our study faces difficult endogeneity challenges that could undermine any causal interpretation of these findings. For instance, it is possible that various environment-related firm policies, rather than solely climate patents, serve as magnets for new business customers. Concerns about selection effects and simultaneity further compound these challenges. To address the risks related to omitted variable bias in the acquisition of new customers, we introduce two distinct instrumental variables: patent examiner leniency (Section 5.1) and technology obsolescence (Section 5.2).

5.1 Patent Examiner Leniency

Our first identification strategy leverages quasi-random shocks in the probability of patent approvals. We posit that the granting of climate patents has a significant signaling effect in attracting new customers.[38] 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

[38] Since 2001, the USPTO has been required to publish most patent application documents 18 months after their filing date. However, we argue that customers generally do not carefully examine the publication details in the USPTO patent publication system. Therefore, in this section, we use the patent granting date to construct our primary explanatory variable, the climate patent ratio. We thank Alminas Zaldokas for alerting us to this issue.

(Sampat and Williams, 2019; Farre-Mensa, Hegde, and Ljungqvist, 2020).[39] Hence, we use 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 shock is likely to be orthogonal to any remaining ESG-related firm practices (other than climate patents) that aid in attracting new customer firms.

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

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

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 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 grant-

[39]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.

ing ratio of the art unit to which the application is assigned and to which examiner e belongs: $\frac{\text{Num\_Pat\_Granted}_a - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_a - 1}$. Hence, our leniency measure is a relative leniency measure within an art unit. Table A2 offers summary statistics of this IV sample.[40]

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

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

For each year, we conduct a sample split among all new customer firms based on the annual median environmental score. Subsequently, we define two new dependent variables: the count of new customers with high and low environmental scores, detailed in Panels A (columns (6) – (8)).[41] Similarly, Panel B deploys a sample split using total GHG emissions (Scope 1+2). In Table 11, we find exactly the same results as in Table 7: (i) Supplier's climate innovation becomes a catalyst for attracting new customers post-2010; (ii) this effect is magnified for new customers with high environmental scores and elevated emissions. These outcomes should alleviate concerns regarding omitted variable bias and bolster the case for a causal interpretation.

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

[41] We use the ln(1+x) transformation for our dependent variables because the alternative of using Poisson regressions faces several critical limitations: (i) Poisson regressions impose strong assumptions on the distribution of the error terms and are subject to issues of under-dispersion or over-dispersion (Wooldridge, 2010); (ii) our empirical model introduces many interaction terms, and in the case of Poisson regressions, the coefficients of interaction terms become difficult to interpret (Shang et al., 2018). (iii) Poisson regressions are difficult to implement in 2SLS regressions.

The examiner leniency instrument aims at studying an exogenous shock in the capacity to attract *new* customers. It relies on random variation in patent grants, with the identifying assumption that the patent award itself matters, not just the usefulness of the underlying technology that is independent of its patent status: climate patents serve as a "certification" for new customers and prevent industry competitors from developing similar technology, but presumably are less important for existing customer relationships. Since the tests in Table 7 focus on the acquisition of new customers where the prestige and visibility of a USPTO grant likely matters, this is a reasonable assumption (by contrast, in existing supply chain relationships with their often dense communication channels, the technology rather than the patent status should play a greater role). This distinction implies that the leniency instrument will likely not be effective for customers' CO2 emissions (see Table 3), since the effectiveness of the underlying technology and not its patent protection should help in cutting carbon emissions. Indeed, as expected, we find (in unreported regressions) that the examiner leniency shock has no impact on emissions of existing customers.[42]

5.2 Technology Obsolescence

Our second instrument, technology obsolescence, is designed to overcome the limitation in the identifying assumption of examiner leniency that the patent status matters. As it looks at exogenous variations in the underlying technology and not in patent grants, we expect to find effects on customer emissions.

Our instrument 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 should therefore be caused by unexpected technology shocks outside the firm's purview. Thus, the obsolescence metric should measure technology shocks orthogonal to the innovator's decisions and to customer characteristics or preferences, and hence should help to strengthen the interpretation of causality in the link between climate innovation and customer firms' CO2 emissions. In support of this interpretation, Ma (2022)

[42]This finding is in line with the evidence in Hege et al. (2024) (using the same examiner leniency IV) that only the underlying technology and not the patent grant decision affects carbon emissions of climate innovators.

shows that technology obsolescence overwhelmingly measures technology-specific shocks that vary widely within each firm, not firm-specific variations.

We construct the instrumental variable, technology obsolescence, by partitioning each firm's patent stock (cumulative historical patents with applications up to year t that are eventually granted) 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. Therefore, our measure isolates 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,

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

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, calculated following Ma (2022). Specifically, firm i's climate patent stock in year t includes all (Y02) climate patents of firm i with applications since 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. We then compute the annual citations in year $t-5$ and in year t within this knowledge space. 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 Panel A in Table 12, demonstrates a significant negative association between *Tech_Obsolescence_Diff* and 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. These findings confirm 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 causal interpretation, we replicate the methodology used in Table 5, and construct a supplier-customer pair sample with pair fixed effects, implemented in reduced-form 2SLS regressions. The results are presented in Panel B of Table 12. 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 compared with its industry peers. 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.

To conclude, our two instruments offer complementary perspectives, the first focusing on patent grants (hence on exogenous variations in the appeal to new customers), the second on technology obsolescence (hence on exogenous variations in technology that also affects customer emissions). They show strong evidence in support of a causal view of our main findings. Viewed alongside our earlier tests addressing concerns about selection effects, namely the documented emission reductions following climate innovation in stable supply chain pairs (Section 3.2) and the emission reduction observed for newly acquired customers (Section 4.3), they should alleviate endogeneity concerns.

6 Conclusion

We study the impact of climate innovation (identified with the "Y02" scheme) on carbon emissions and business expansion, focusing on the innovator's downstream supply chain network. Specifically, we explore whether climate innovation invented by a supplier firm allows its customer firms to reduce CO2 emissions (intensive margin channel), and whether climate innovation facilitates the acquisition of new business customers and their subsequent emission cuts (extensive margin channel). Only the combined study of both channels allows a full appraisal of the carbon emission benefits of innovation.

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 heightened for high-emission firms and firms with stronger environmental concerns. We study the extensive-margin dynamics of supply chains in 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 and that climate innovation allows suppliers to expand their customer base. We find that the propensity to switch supply chain links to climate innovators is more pronounced for high-emission customer firms and firms with high environmental scores. We show strong evidence that the association between climate patents and customer emissions reductions is causal, using panel regressions of stable supply chain relationship, the emission reductions of new customers, and two complementary instrumental variables on exogenous variations in patent grants and technological obsolescence.

The widely held view of innovation as an indispensable tool of climate change mitigation has led to numerous public policies, including subsidies for producers and customers, aimed at fostering incentives for the development and adoption of new climate technologies. But since the benefits of such technology-related policies are not firmly established, our finding that climate innovation is effective in reducing carbon emissions along the supply chain and changes the dynamics of supply chain relationships, as well as our methodological contributions to the study of these links, should be of interest to policy makers designing and evaluating these policies.

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A Variable Definitions and Construction

Variable Name	Definition of Variable	Data Source
Customer Firm × Year Sample – Table 3, 4, 8		
GHG Emissions (Scope 1) – Total	natural logarithm of greenhouse gas emissions in tons (Scope 1) emitted by firm i in year t	S&P Trucost
GHG Emissions (Scope 1) – Intensity	natural logarithm of greenhouse gas emission intensity (total emissions scaled by sales) (Scope 1) emitted by firm i in year t. Sales are adjusted by 2000 CPI in the US.	S&P Trucost
GHG Emissions (Scope 2) – Total	natural logarithm of greenhouse gas emissions in tons (Scope 2) emitted by firm i in year t	S&P Trucost
GHG Emissions (Scope 2) – Intensity	natural logarithm of greenhouse gas emission intensity (total emissions scaled by sales) (Scope 2) emitted by firm i in year t. Sales are adjusted by 2000 CPI in the US.	S&P Trucost
Supplier's Climate Patent Ratio	weighted climate patent ratio of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate patents newly filed divided by the total number of patents filed in year t	PatentsView
Supplier's Number of General Patents	weighted number of general patents of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The number of general patents is the total number of patents (ultimately granted) filed by a firm in year t, and we use the $\ln(1+x)$ transformation.	PatentsView
Customer's Climate Patent Ratio	climate patent ratio of the customer firm in the observation	PatentsView
Supplier's Climate Patent Ratio (Process Patents)	weighted climate patent ratio (only process patents) of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate process patents (ultimately granted) newly filed divided by the total number of process patents filed in year t	PatentsView
Supplier's Climate Patent Ratio (Product Patents)	weighted climate patent ratio (only product patents) of all suppliers selling products or services to the given customer in year t. The weight assigned to each supplier is based on their sales to the customer. The climate patent ratio is calculated as the number of climate product patents (ultimately granted) newly filed divided by the total number of product patents filed in year t	PatentsView
I[New Supplier with Climate Patents]	dummy variable equal to 1 if the firm obtains a new supplier with a climate patent ratio greater than 0.2. The climate patent ratio is calculated using the supplier's patent information from years $t-2$, $t-1$, and t	PatentsView

Continued on next page

Appendix A continued from previous page

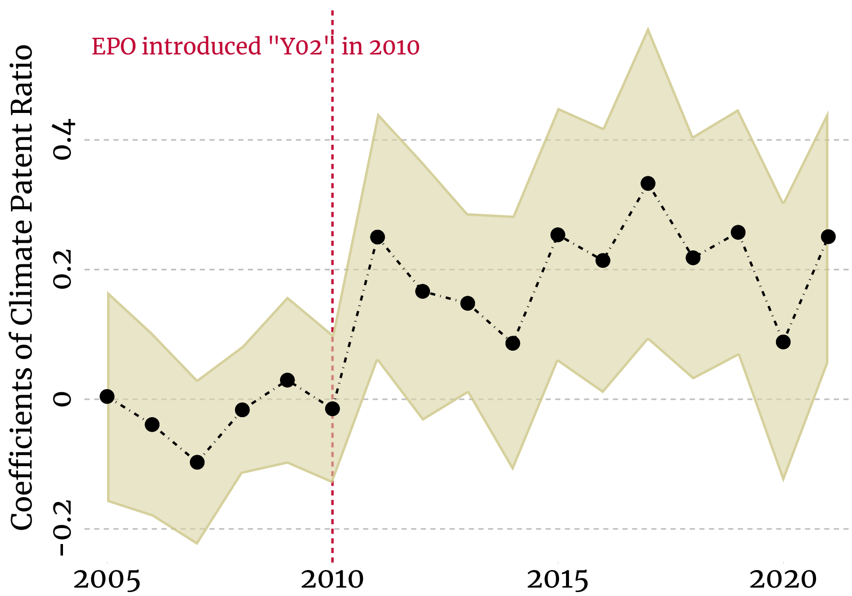
Variable name	Definition of variable	Data Source
I[Old Supplier with Climate Patents]	dummy variable equal to 1 if the firm has long-standing suppliers (relationships starting 5 years ago) with a climate patent ratio (in years $t-2$, $t-1$, and t) greater than 0.2	PatentsView
Firm Size (MarketCap)	firm size, measured as natural logarithm of the firm's market capitalization (Compustat item $CSHO_t$ × item $PRCC\_F_t$)	CRSP-Compustat
Tobin's Q	Market-to-book ratio in assets. Market value of assets equals the book value of assets (item AT_t) + the market value of common equity at fiscal year-end (item $CSHO_t$ × item $PRCC\_F_t$) − the book value of common equity (item CEQ_t) − balance sheet deferred taxes (item $TXDB_t$)	CRSP-Compustat
R&D	R&D expenditure, measured as item XRD_t scaled by lagged book assets (item AT_{t-1}). If this variable is missing, we replace it with the industry-year median R&D expenditure.	CRSP-Compustat
Cash	defined as cash and cash equivalents (item CHE_t) scaled by lagged book assets	CRSP-Compustat
ROA	return on assets, defined as EBITDA scaled by lagged book assets	CRSP-Compustat
Book Leverage	book leverage, defined as debt including long-term debt (item $DLTT_t$) plus debt in current liabilities (item DLC_t) divided by the sum of debt and book value of common equity (item CEQ_t)	CRSP-Compustat
CAPX	capital expenditure, measured as item $CAPX_t$ scaled by lagged book assets	CRSP-Compustat
PPE	natural logarithm of firm's value of plants, properties, and equipment (PPE)	CRSP-Compustat
Discrete Choice Model Sample – Table 6		
I(Supplier-Customer Match) [Dependent Variable]	dummy variable equal to 1 if the customer firm c selects the supplier firm s to purchase goods or services in year t	FactSet
Supplier's Climate Patent Ratio [t-1]	supplier's climate patent ratio in year $t-1$. Climate patent ratio is the ratio of climate patents among all patents filed by the supplier. We calculate patents here using patent application year	PatentsView
Supplier's Num General Patents	number of general patents filed by a supplier	PatentsView
I(Post 2010)	dummy equal to 1 after 2010 (not including 2010)	
I(Before 2010)	dummy equal to 1 before 2010 (including 2010)	
Customer's Environmental Score	customer firm's environmental score	MSCI and Refinitiv
Customer's Social Score	customer firm's Social score	MSCI and Refinitiv
Customer's Governance Score	customer firm's Governance score	MSCI and Refinitiv

Continued on next page

Appendix A continued from previous page

Variable name	Definition of variable	Data Source
Supplier × Year Sample – Figure 1 and Table 7, 9, 11, and 12		
Number of New Customer Firms	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before	FactSet
Number of New Customer Firms (with High E-Score)	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before. For each year, we sort all new customer firms into two groups by median. Customer firms with high E-score are firms with above median environmental ratings.	FactSet
Number of New Customer Firms (with High Emissions)	number of new customer firms starting to purchase products and services from the supplier firm f in year t. New customers are defined as firms never having purchased before. For each year, we sort all new customer firms into two groups by median. Customer firms with high emissions are firms with above median emission intensity.	FactSet

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

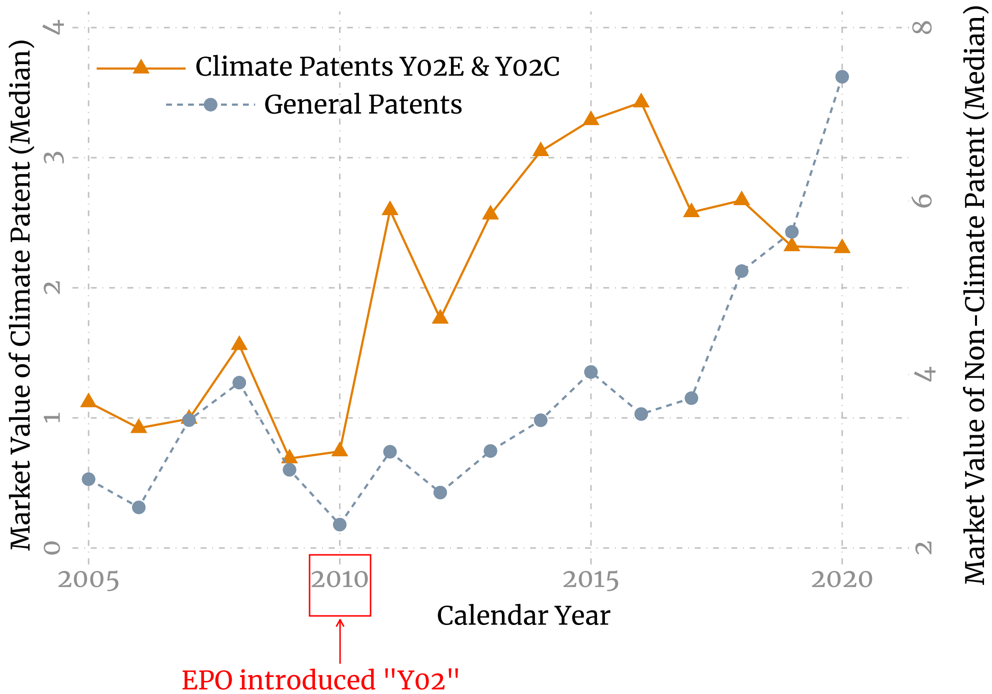


This figure examines the relationship between the climate patent ratio and the number of new customers attracted by each supplier firm. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

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

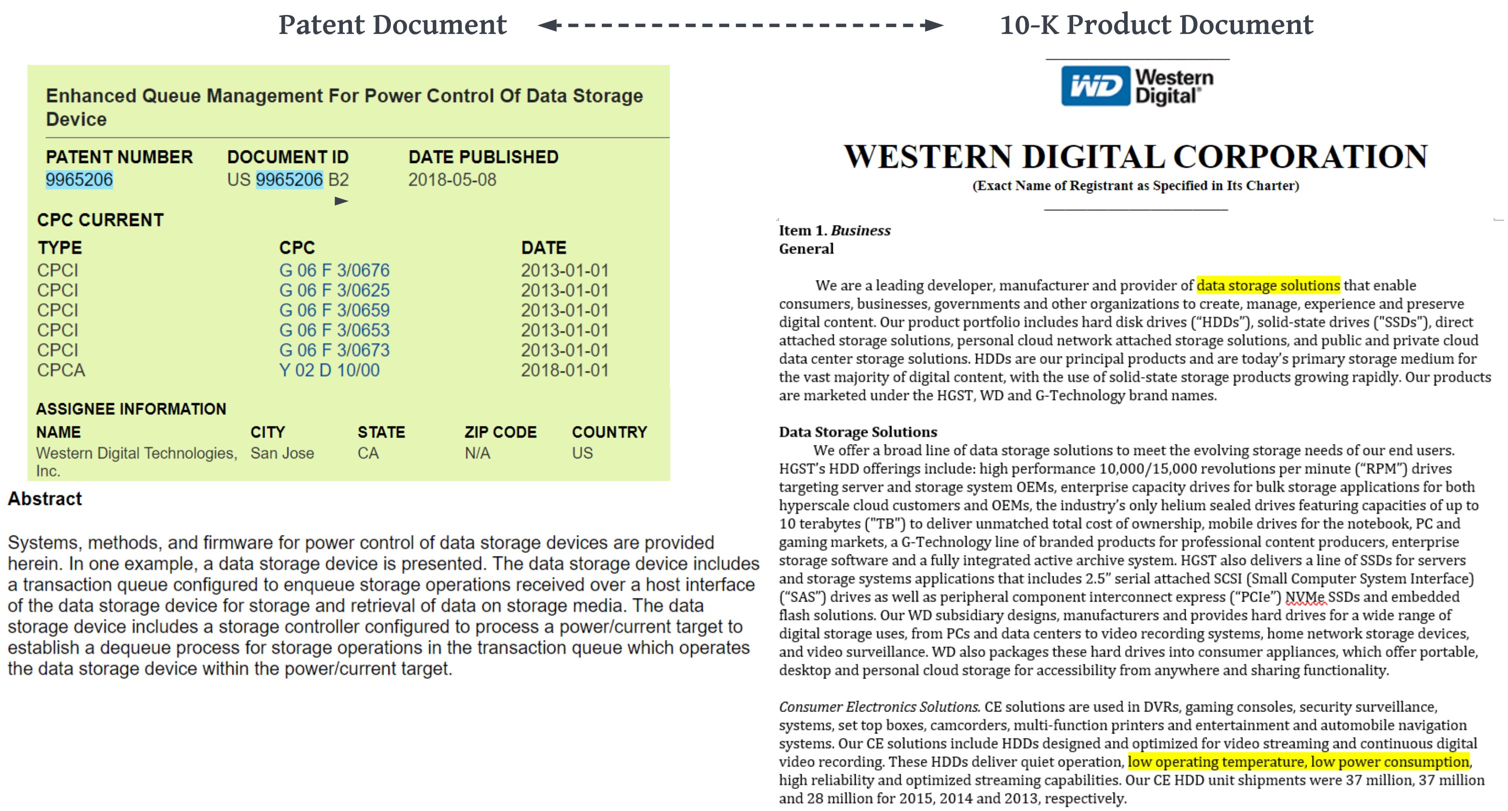
where $Num\_New\_Customer\_Firms_{i,t}$ signifies the count of newly attracted customer firms establishing supplier-customer relationships with firm i in year t. The dependent variable is transformed using the natural logarithm of $(1+x)$. The variable $Clim\_Patent\_Ratio_{i,\mathbf{t\text{-}1}}$ represents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



Enhanced Queue Management For Power Control Of Data Storage Device

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

CPC CURRENT

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

ASSIGNEE INFORMATION

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

Abstract

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

WESTERN DIGITAL CORPORATION

(Exact Name of Registrant as Specified in Its Charter)

Item 1. ***Business***
General

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

Data Storage Solutions

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

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

This figure 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: Supplier-Customer Relationships

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

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

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. Log denotes the $ln(1 + x)$ transformation.

Panel A: Customer Sample

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

Panel B: Compustat Sample (Suppliers)

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

Panel C: Pairwise Correlations among Environmental Scores of Different Providers

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

Panel D: Pairwise Correlation between ESG Scores and Emissions

Pairwise Correlation

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

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

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

Panel A: Scope 1 CO2 Emissions

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

Panel B: Scope 2 CO2 Emissions

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

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

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

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

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

Panel B: Interaction with Prior Customer Emissions

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

Panel C: Product Patents vs. Process Patents

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

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

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

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

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

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

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

Table 6. 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) suppliers that are selected by the given customer firm and (ii) 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] × Customer's GHG Emissions (Total) [t] × I(Before 2010)								0.004 (0.003)	
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Intensity) [t] × I(Post 2010)									0.014*** (0.002)
Supplier's Climate Patent Ratio [t-1] × Customer's GHG Emissions (Intensity) [t] × I(Before 2010)									0.005* (0.002)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Customer Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
Supplier NAICS-4 F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	1696323	1696323	1696323	1668520	1696323	1466725	1466725	1466725	1466725
Adjusted R^2	0.065	0.065	0.065	0.065	0.065	0.069	0.069	0.069	0.069

Table 7. 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. Panel D explores possible customer departures subsequent to climate innovation by their suppliers. The dependent variable is the number of firms that cease purchasing products or services from the specified suppliers. These customers are divided into two groups based on their environmental scores: those with high scores and those with low scores. Firm controls include firm size, Tobin's Q, cash, book leverage, ROA, capital expenditure, sales growth, and the number of existing customers (all measured in year $t-1$). Industry (NAICS 4-digit) fixed effects are included in columns (1) to (3), and firm F.E. are added in columns (4) to (6). Standard errors are clustered at the firm level. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A: Customer Firms Split by Environmental Score

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

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

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

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

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

Panel D: Existing Customers' Possible Departure

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

Table 8. Customer's CO2 Emission Reductions: New and Old Suppliers

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

Panel A: Scope 1 CO2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
I[New Supplier with Climate Patents]	-1.986	-0.922	-5.022*	-4.474*	-8.548***	-6.593**	-9.765**	-7.182*	-11.134**	-10.476**
	(1.586)	(1.417)	(2.732)	(2.488)	(3.134)	(3.055)	(4.249)	(3.907)	(4.614)	(4.261)
I[Old Supplier with Climate Patents]	-1.743	-1.830	-3.370	-3.396*	-5.597**	-6.573***	-1.770	-4.763	-2.610	-5.774
	(1.615)	(1.413)	(2.353)	(2.040)	(2.816)	(2.521)	(3.884)	(3.282)	(4.958)	(4.311)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry $\times$ Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	15849	15526	13541	13229	11476	11188	9573	9316	7812	7593
Adj. R^2	0.015	0.030	0.046	0.036	0.059	0.041	0.071	0.058	0.092	0.081

Panel B: Scope 2 CO2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 2 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
I[New Supplier with Climate Patents]	-3.226*	-2.273	-6.064**	-5.389**	-7.959**	-5.048	-10.968**	-8.039**	-16.916***	-16.025***
	(1.693)	(1.444)	(2.736)	(2.425)	(3.631)	(3.232)	(4.302)	(3.824)	(5.887)	(5.678)
I[Old Supplier with Climate Patents]	-1.973	-1.798	-5.563**	-5.510**	-6.330**	-6.332**	-6.301	-7.591	-5.490	-4.363
	(1.630)	(1.404)	(2.639)	(2.346)	(3.205)	(2.755)	(5.073)	(4.656)	(7.326)	(6.689)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry $\times$ Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	15856	15533	13547	13235	11479	11191	9577	9320	7816	7597
Adj. R^2	0.065	0.060	0.108	0.085	0.136	0.116	0.173	0.149	0.216	0.192

Table 9. Climate Innovators and Operating Performance

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

Operating Performance of Climate Innovators (Sales and Profits)

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

Table 10. Climate Patent Ratio and New Customer Firms (Extension)

This table presents extensions of Table 7. 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 $\cdots$				
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 $\cdots$				
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 $\cdots$				
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 11. Climate Patent Ratio and New Customer Firms (Examiner Leniency as Instrument)

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

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

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

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

$\frac{\text{Num\_Pat\_Granted}_e - I(\text{Granted})_p}{\text{Num\_Pat\_Examined}_e - 1}$ 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: Customer Firms Split by Environmental Score

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

Panel B: Customer Firms Split by CO2 Emissions

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

Table 12. Climate 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,

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

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) with applications filed 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.

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

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: Acquisition of 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 (*Instrumental Variable*)	-0.014*** (0.004)				
$\widehat{\textit{Climate Patent Ratio}}$ [t-1] (*Instrumented by Tech. Obsolescence Diff.*)		1.627*** (0.619)	0.341 (0.751)	1.531** (0.600)	0.309 (0.785)
Number General Patents [t-1]	0.087*** (0.005)	-0.035 (0.029)	0.001 (0.022)	-0.015 (0.022)	0.004 (0.019)
Number Existing Customers [t-1]	0.006 (0.005)	0.365*** (0.026)	0.314*** (0.016)	0.224*** (0.025)	0.209*** (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

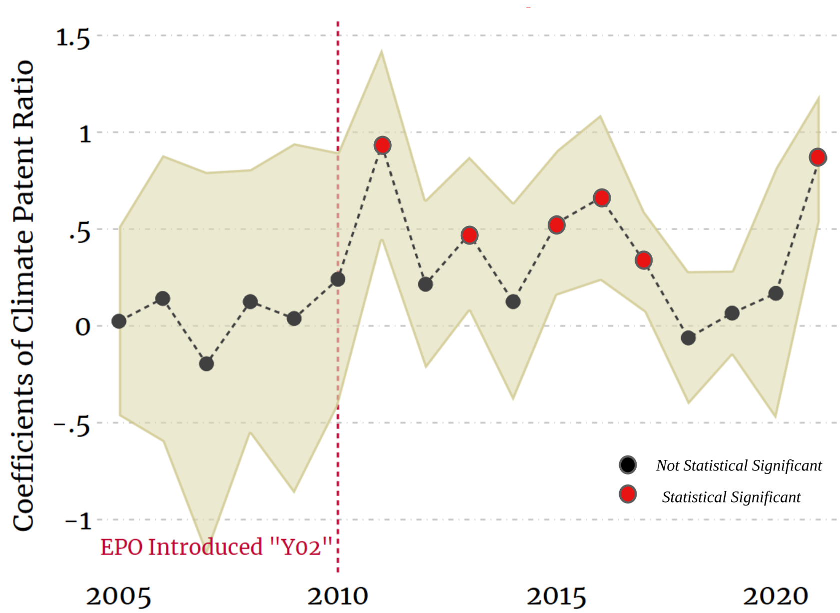
	(1)	(2)	(3)	(4)	(5)	(6)
Emissions by Customer Firm	Scope 1 Emission Total			Scope 2 Emission Total		
Measured in	$t+3$	$t+4$	$t+5$	$t+3$	$t+4$	$t+5$
Supplier's Tech. Obsolescence [t] (Climate Innovation)	3.690** (1.709)	3.993** (1.982)	3.779* (2.274)	4.377* (2.356)	3.352 (2.910)	0.066 (4.095)
Customer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

Empirical Results Not Included in the Paper

Figure A1. Supplier's Climate Patent Ratio and Number of New-Attracted Customer Firms – Poisson Regression

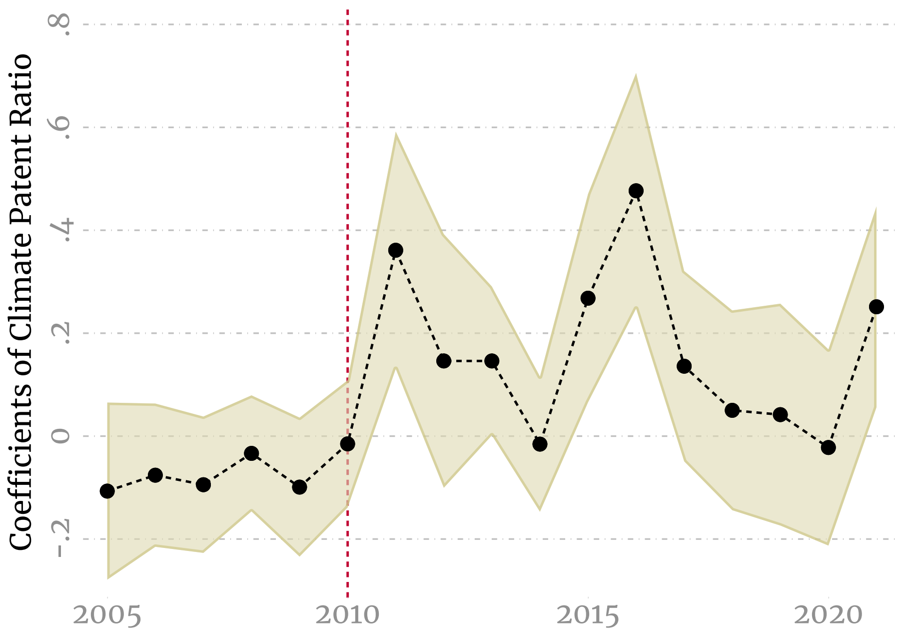


This figure examines the relationship between the climate patent ratio and the number of new customers attracted by each supplier firm. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

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

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 granted to the firm to all patents granted to 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 A2. Supplier's Climate Patent Ratio and Number of New-Attracted Customer Firms – Use Patent Application Year

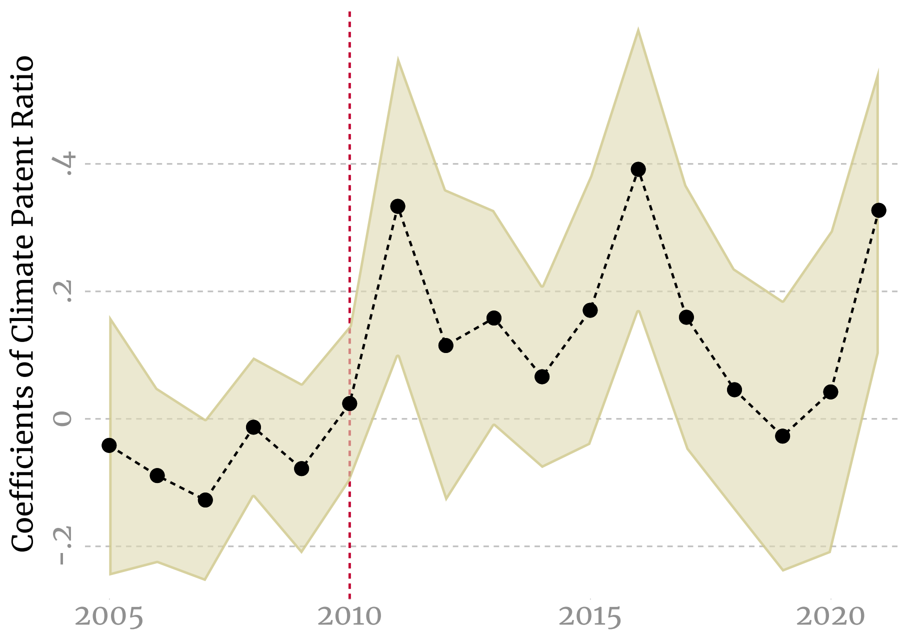


This figure offers robustness checks for Figure 1. We use the patent application dates instead of the granting dates to construct the climate patent ratio. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t \Big) + \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (16)$$

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 variable $Clim\_Patent\_Ratio_{i,\mathbf{t\text{-}1}}$ represents the ratio of climate-related patents (Y02) of firm i with application filed in year $t-1$ that are ultimately granted to all patents filed by the same firm in year $t-1$ (and ultimately granted). 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 A3. Supplier's Climate Patent Ratio and Number of New-Attracted Customer Firms – Use Both Granted and Rejected Patents



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This figure offers robustness checks for Figure 1. We include both granted and rejected patent applications to construct the climate patent ratio. The coefficients of $\beta_{1,Year}$ in the following regression equation are visualized in the figure:

$$\text{Num\_New\_Customer\_Firms}_{i,t} = \sum_{Year=2005}^{2021} \beta_{1,\text{Year}} \Big(\text{Clim\_Patent\_Ratio}_{i,\mathbf{t\text{-}1}} \times I(\text{Year})_t \Big) + \beta_2 \text{Num\_General\_Patent}_{i,\mathbf{t\text{-}1}} + \beta_3 X_{i,t-1} + \chi_{\text{NAIC-4},t} + \varepsilon_{i,t} \quad (17)$$

Where $Num\_New\_Customer\_Firms_{i,t}$ signifies the count of newly attracted customer firms by firm i in year t. The variable $Clim\_Patent\_Ratio_{i,\mathbf{t\text{-}1}}$ represents the ratio of climate-related patents (Y02) with applications filed by firm i in year $t-1$ to all patents filed 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) × year fixed effects are included. Standard errors are clustered at the firm level, and the confidence intervals depicted in the figure denote a 90% confidence level.

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

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

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

Table A2. Additional Summary Statistics

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

Panel A: Pairwise Correlations among New Customer's Characteristics

Pair-wise Correlation

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

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

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

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

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

Panel A: Scope 1 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Number [t]	-2.059	-2.032	-6.387**	-6.153**	-9.701**	-9.603**	-12.563**	-12.041**	-12.238**	-13.178**
	(1.574)	(1.545)	(2.766)	(2.508)	(3.997)	(3.795)	(4.962)	(4.770)	(5.562)	(5.627)
Supplier's General Patent Number [t]	0.599	0.241	3.576	3.529	5.017	5.336	5.722	5.471	4.770	5.003
	(1.551)	(1.412)	(2.713)	(2.363)	(4.204)	(3.874)	(5.449)	(5.122)	(6.797)	(6.512)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.109	0.077	0.168	0.123	0.204	0.143	0.242	0.196	0.324	0.256
Panel B: Scope 2 Emissions										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 2 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Number [t]	-2.887*	-2.600**	-6.396**	-5.992***	-7.506**	-6.945***	-8.403*	-7.398**	-5.760	-5.867
	(1.514)	(1.293)	(2.508)	(1.911)	(3.347)	(2.520)	(4.378)	(3.253)	(5.427)	(3.765)
Supplier's General Patent Number [t]	1.982	1.323	4.254*	3.722*	4.898	4.673	4.941	3.861	0.730	0.565
	(1.439)	(1.249)	(2.490)	(2.095)	(3.505)	(2.850)	(4.536)	(3.693)	(5.384)	(4.519)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry × Year F.E.	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Num. Obs.	1796	1735	1773	1702	1616	1546	1465	1396	1319	1250
Adjusted R^2	0.110	0.079	0.165	0.121	0.202	0.142	0.239	0.192	0.323	0.254

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

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

Panel A: Scope 1 CO2 Emissions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Change of Scope 1 CO2 Emissions	t+1 - t		t+2 - t		t+3 - t		t+4 - t		t+5 - t	
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t-2, t-1, t]	-2.812**	-3.168***	-4.271*	-4.702**	-6.647**	-7.598***	-7.566**	-9.010***	-9.370***	-11.123***
	(1.320)	(1.161)	(2.314)	(1.895)	(2.638)	(2.034)	(3.175)	(2.665)	(3.599)	(3.332)
Supplier's Number of General Patent [t-2, t-1, t]	0.375	0.070	1.005	1.142	0.723	1.321	-0.740	0.351	-1.244	-0.788
	(1.128)	(1.075)	(2.184)	(1.935)	(3.199)	(2.793)	(4.109)	(3.626)	(4.980)	(4.742)
Customer's Climate Patent Ratio [t-2, t-1, t]	2.980**	2.337**	4.506**	3.627**	3.401	2.860	3.771	3.659	3.761	1.117
	(1.218)	(0.937)	(1.945)	(1.744)	(2.450)	(2.116)	(3.540)	(3.010)	(4.293)	(3.715)
Customer Firm Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry $\times$ 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

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

Table A5. 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) $\times$ 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: Customer Firms in Coal Mining, Manufacturing, and Transportation

Change in Scope 1 CO2 Emissions	(1) t+1 - t	(2)	(3) t+2 - t	(4)	(5) t+3 - t	(6)	(7) t+4 - t	(8)	(9) t+5 - t	(10)
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-2.361**	-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 $\times$ 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

Change in Scope 1 CO2 Emissions	(1) t+1 - t	(2)	(3) t+2 - t	(4)	(5) t+3 - t	(6)	(7) t+4 - t	(8)	(9) t+5 - t	(10)
Emissions by Customer Firm	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity	Total	Intensity
Supplier's Climate Patent Ratio [t]	-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 $\times$ 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 A6. 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 A7. 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 A8. 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 A9. Robustness Check for Table 7 (Post-2010 Sample Only)

This table provides the robustness checks for Table 7 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, $Climate\ Patent\ Ratio_{t-1}$, 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 A10. 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