Climate vulnerability and corporate innovation: International evidence

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This version: February 2021

Abstract

Using firm-level R&D and patent data for 88 countries, we find that country climate vulnerability negatively affects firms' R&D investment and innovation performance. This effect operates through the decreased responsiveness of R&D investment to investment opportunities (i.e., investment efficiency), reduced incentives to innovate, and lower private value of new innovations. The effect is more pronounced for firms with longer product development cycles and more attentive to climate change and exists in both developed and developing countries. The silver lining is that climate vulnerability increases the ratio of patents on climate change mitigation technologies (CCMTs) in innovations. Finally, we find similar results when using climate-related natural disasters as an identification strategy. Overall, our findings suggest that climate vulnerability hinders corporate innovation activities in general, but it also facilitates innovation in CCMTs.

JEL classification: F20; G32; G15; O31; Q55

Keywords: climate vulnerability; R&D; patents; innovation; climate risk; climate change

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We thank Pedro Matos for sharing the global corporate patent dataset. Any errors are ours.
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1. Introduction

Climate change has become one of the most pressing issues of our time. Global warming and more frequent extreme weather events substantially impact society and the economy (e.g., Stern, 2008; Intergovernmental Panel on Climate Change, 2014, 2018). For example, the global economic growth rate is reduced by roughly 0.25 and 1.3 percentage points per year due to temperatures and tropical cyclones (Burke, Hsiang, and Miguel, 2015; Carleton and Hsiang, 2016). Despite the massive economic effects, there is a lack of comprehensive evidence on the mechanisms for the long-term economic growth effects of climate change.[1] In this study, we propose a mechanism from a corporate innovation perspective, one of the key determinants of productivity growth (e.g., Griliches, 2007; Kung and Schmid, 2015) that may explain the adverse growth effects of climate change. Specifically, we investigate how climate vulnerability influences corporate R&D investment and innovation output around the world.

Climate vulnerability is the propensity or predisposition to be adversely affected by climate change and comprises sensitivity or susceptibility to harm (IPCC, 2014). It also represents the lack of capacity to cope with and adapt to climate change, thereby determining how severe the climate change impacts could be for an entity. A recent Deloitte survey of 1,168 financial executives across Europe shows that most companies perceive significant pressure of climate change. But few have a governance and steering mechanism in place to develop and implement comprehensive climate strategies.[2] As vulnerability to climate hazards poses a threat to firm survival and growth, and innovation is a critical strategy for sustainable development, our paper provides the first

[1] Previous studies suggest that climate change could affect economic growth rate through its impacts on capital accumulation and people's propensity to save as well as labor productivity (e.g., Fankhauser and Tol, 2005; Graff Zivin and Neidell, 2014).
[2] See the Deloitte European CFO survey in 2019 (https://www2.deloitte.com/us/en/insights/topics/strategy/impact-and-opportunities-of-climate-change-on-business.html).

comprehensive cross-country analysis that has important practical implications for policymakers and managers.

The gist is that climate change creates new business risks that may impair firm performance and profitability. For example, climate variability and extreme events (e.g., drought, flooding, heatwaves, storms, etc.) can disrupt companies' supply chains and business operations, reduce asset value and earnings, increase operational costs (e.g., relocation costs and insurance costs), and affect business sustainability.[3] Besides the most obvious physical risks, firms are exposed to transition risks that arise from society's response to climate change, such as changes in technologies, markets, and policies and regulations that can increase business costs, undermine the viability of existing products/services, or hurt the value of investments.[4] The costs and risks associated with climate change may severely impact companies' bottom lines, increase uncertainty about investment returns, and accentuate the financial risks associated with innovation and R&D activities.

Meanwhile, motivating innovation is challenging for most firms (e.g., Manso, 2011; He and Tian, 2013), as innovation is a risky and costly investment with long-term uncertain payoffs and a

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[3] For example, drought and water scarcity could cause increased production costs or production disruptions and reduce revenues for semiconductor companies, as manufacturing semiconductors requires large volumes of ultra-pure water. This also affects many other companies as semiconductors are essential components of electronic devices. For companies in the software and services industry, especially those who operate data centers that consume large amounts of energy, the rising temperatures make energy-consuming facilities and equipment more expensive to cool and increases operating costs. The severe flooding across Thailand in 2011 disrupted Western Digital Technologies' manufacturing of hard disk drives and caused revenue loss and global industry supply shortages and elevated component costs for almost two years with severe reverberations for computer manufacturers. U.S. drugmaker Eli Lilly reported that climate change could financially hurt the firm if fiercer storms destroy its manufacturing facilities, as happened after Hurricane Maria in 2017. According to a New York Times report, 215 biggest global companies, from Silicon Valley tech firms to large European banks, are bracing for the impacts of climate change on their bottom lines within the next five years, and estimate at least $250 billion in losses due to the write-offs of assets and trillions of dollars at risk (https://www.nytimes.com/2019/06/04/climate/companies-climate-change-financial-impact.html).

[4] For example, as climate-related regulations drive up the cost of energy, high-tech and renewable-energy industries face price risks in the competition for rare earths and higher R&D costs for improving energy efficiency. Technology companies also face risks from environmental factors such as greenhouse gas emissions, waste and pollution from manufacturing, and disposal of old products, which increase operating costs and capital expenditures to deal with these issues and also put companies at a higher risk of regulatory fines and lawsuits. Shifts in consumer demand may require a company to modify or entirely drop a product line.

high probability of failure. Previous studies show that uncertainties, such as policy uncertainty, uncertain returns on innovation, and cash flow volatility, make firms more cautious in innovation, leading to underinvestment in R&D (e.g., Minton and Schrand, 1999; Goel and Ram, 2001; Bloom, 2007; Czarnitzki and Toole, 2011; Segal, Shaliastovich, and Yaron, 2015; Bhattacharya, Hsu, Tian, and Xu, 2017). Hence, high levels of uncertainty inherent in climate change and the uncertainty of climate-related risks may adversely affect firms' incentives to invest in innovative projects. As predicted by theoretical models of investment under uncertainty (e.g., Pindyck, 1991; Dixit and Pindyck 1994; Bloom, Bond, and Van Reenen 2007), an increase in any risk, including the climate-related risks, should decrease firm investment.[5]

Climate-related risks could also reduce firms' capacity to engage in innovation as innovation capacity largely depends on innovation infrastructure, innovation environment, and the availability of resources, such as stable funding and highly skilled labor. However, climate change and extreme weather cause fluctuations in earnings and cash flows, increase financing costs, and adversely affect infrastructure development, labor supply, and labor productivity (e.g., Black and Henderson, 1999; Graff Zivin and Neidell, 2014; Heal and Park, 2016; Huang, Kerstein, and Wang, 2018; Jiang, Li, and Qian, 2020). These shocks would, in turn, result in higher production and R&D costs. The lack of adequate support for innovation could decrease firms' innovation capacity and the consequent poor innovative performance. Taken together, we argue that greater vulnerability to climate change negatively impacts firms' incentives and capabilities to innovate and conduct R&D. Accordingly, we propose our main hypothesis that *firms with higher climate vulnerability have lower levels of R&D investment and innovation performance.*

[5] Consistent with the prediction, Hassan, Hollander, Van Lent, and Tahoun (2019) find that increases in firm-level political risks, which are associated with eight political topics including environment (e.g., climate change, clean air, and global warming), significantly decrease firms' investment, planned capital expenditures, and hiring.

To test our hypothesis, we use the climate vulnerability index from the Notre Dame Global Adaptation Initiative (ND-GAIN).[6] It measures a country's vulnerability to climate disruptions in terms of three dimensions: exposure, sensitivity, and adaptive capacity. Based on a sample of 60,028 publicly listed firms from 88 countries over the period 1995-2019, we find that climate vulnerability in year *t* negatively affects firms' R&D investment in year *t*+1 after controlling for known determinants of R&D, firm fixed effects, and year fixed effects. In terms of economic magnitude, a one-standard-deviation increase in climate vulnerability leads to a 0.7 percentage points decrease in R&D investment, which corresponds to a 48% decrease relative to the mean of R&D-to-assets ratio or a 14.1% decrease relative to the standard deviation. The result reveals that firms located in countries with higher climate vulnerability tend to be more cautious and conservative in R&D investment.

We then examine how climate vulnerability affects firm innovation performance by using comprehensive firm-level patent data from the United States Patent and Trademarks Office (USPTO). Our results show that climate vulnerability has significant negative effects on the number of patents a firm generates (quantity of innovation) and the number of citations these patents receive subsequently (quality of innovation), suggesting that climate vulnerability is detrimental to firm innovation performance.

We further explore the possible channels through which climate vulnerability hinders corporate innovation. First, we analyze investment efficiency using the responsiveness of R&D investment to investment opportunities (e.g., Badertscher, Shroff, and White, 2013; Zhong, 2018) and find that the responsiveness decreases with climate vulnerability. The result suggests that climate vulnerability makes firms forgo investment opportunities (i.e., less willing to take risky

[6] The ND-GAIN Country Index is compiled and published by the University of Notre Dame, a time-series index for assessing the impact of climate change since 1995 (https://gain.nd.edu/our-work/country-index/).

projects) and leads to inefficient allocation of R&D investment. This result is consistent with previous findings that when uncertainty is high, firms become cautious and hold back on irreversible investment and adopt a wait-and-see strategy, thereby reducing responsiveness to investment opportunities (e.g., Bloom et al., 2007; Julio and Yook, 2012).

Second, we follow the methodology of Bhattacharya Hsu, Tian, and Xu (2017) and find that inventors' incentives to innovate (proxied by the number of patenting inventors) are severely affected by climate vulnerability. Perhaps because climate-related risks and uncertainties increase the costs, risks, and uncertainties of R&D, and when uncertainties are not addressed explicitly, decision-makers may choose for inaction despite investment being profitable (e.g., Abadie, Chamorro, and González-Eguino, 2013). This finding supports our interpretation that climate vulnerability lowers firms' incentives to engage in R&D and innovation activities, which leads to underinvestment in innovation.

Third, climate change risk is shown to lower asset valuations (e.g., Hong, Li, and Xu, 2019; Bansal, Kiku, and Ochoa, 2019), increase R&D costs, and cause technology and market uncertainty that reduces the prospect of patent commercialization. Hence, it may also impair the private return to R&D or the economic value of new innovations. Indeed, our result shows that climate vulnerability negatively affects the patent grant announcement returns and the market value of new patents, which indicates that climate vulnerability weakens the contribution of innovation to firm valuation. This finding also helps explain the reduced incentives to invest in R&D and innovation.

To better understand the effect of climate vulnerability on R&D investment, we conduct several subsample analyses. Our result shows that this effect is more pronounced when managers face greater ex-ante career risks of investing in R&D when they work in firms with longer product development cycles. We also find a stronger effect for the firms paying more attention to climate change, measured by the Google search volume index of the topic "Climate variability and change" in a country. This result is consistent with Sautner, van Lent, Vilkov, and Zhang (2020) who show that greater attention to climate change is associated with a rise in firms' exposures to physical and regulatory climate shocks. Moreover, the effect exists in both developed and developing countries, indicating that our main result is not driven by developing countries that are likely to be vulnerable to climate change due to lower adaptive capacity.

We also consider whether companies explore business opportunities arising from climate change. To achieve competitive advantages, some companies may choose to improve their resource productivity to reduce costs, shift towards renewable energy, and develop sustainable technologies and green products/services. We find that climate vulnerability increases the ratio of patents on climate change mitigation technologies (CCMTs) in new innovations. Although climate vulnerability reduces investment in R&D in general, it does facilitate certain firms to adopt new technologies or applications for mitigation or adaptation against climate change.

In addition, we follow prior studies (e.g., Manso, 2011; Custódio, Ferreira, and Matos, 2019) and classify patents into exploitative (i.e., patents that refine and extend existing knowledge) and exploratory (i.e., patents that require new knowledge or departure from existing knowledge and provide uncertain and distant returns). We find that climate vulnerability is negatively (positively) associated with the ratio of exploratory (exploitative) patents, suggesting that firms with greater climate vulnerability pursue less risky innovation strategies.

To identify the causal effect of climate change on firm innovation, we rely on climate-related natural disasters, including the 2003 European heatwave (especially in France), the 2004 Asian tsunami, the 2011 Japan's earthquake and tsunami, and the 2011 Thailand's flooding. Using a difference-in-differences (DID) regression analysis, we find that firms in treated countries invest significantly less in R&D after the natural disaster. This evidence supports the causal interpretation of climate vulnerability on firm R&D and innovation.

Finally, we find qualitatively similar results when we use firm-level measures of climate change exposure constructed by Sautner, van Lent, Vilkov, and Zhang (2020) and the Global Climate Risk Index developed by Germanwatch. We also find a positive relation between firm innovation and the Notre Dame-Global Adaptation Index (computed by subtracting the vulnerability score from the readiness score for each country), indicating that the adverse impacts of climate vulnerability can be mitigated by more adaptation actions. Our results are robust to alternative measures of R&D and innovation, models with different fixed effects, and subsamples of non-U.S. firms, firms with at least one patent application during the sample period, and the period of 1995-2017 for the truncation issue due to the patent application-grant lag.

Our study contributes to the literature in several ways. First, it adds to the literature on climate change and its economic impacts (e.g., Dell, Jones, and Olken, 2014; Burke, Hsiang, and Miguel, 2015; Carleton and Hsiang, 2016; Hsiang and Kopp, 2018). We complement this literature by showing that climate vulnerability hinders corporate innovation worldwide, pinning down a potential mechanism through which climate change slows economic growth. Second, our paper adds to the burgeoning research on climate risk and firm decisions and outcomes (e.g., Huang, Kerstein, and Wang, 2018; Chang et al., 2018; Li et al., 2020; Bai et al., 2020; Flammer, Toffel, and Viswanathan, 2020; Flammer, 2021). Our findings indicate that climate vulnerability lowers firms' incentives to innovate and reduces innovation output. Third, it contributes to the studies on climate change and innovation (e.g., Gans, 2012; Tur-Sinai, 2018) by providing direct evidence that climate vulnerability affects firms' innovation strategies and stimulates innovation in climate change mitigation technologies. Lastly, we extend the innovation literature (e.g., He and Tian, 2013; Chang et al., 2015; Flammer and Kacperczyk, 2016; Bhattacharya et al., 2017; Bena et al., 2017) by demonstrating that climate vulnerability is an important determinant of corporate innovation.

2. Hypothesis development

The literature shows that there is a strong negative relation between uncertainty and firm-level investment (e.g., Alesina and Perotti, 1996; Bloom, Bond, and Van Reenen, 2007; Julio and Yook, 2012; Baker, Bloom, and Davis, 2016). Moreover, if the investment is not fully reversible, it exacerbates the adverse effect of uncertainty on investment (e.g., Pindyck, 1991; Pindyck and Solimano, 1993; Dixit and Pindyck, 1994; Abel et al., 1996; Gulen and Ion, 2016). R&D investment is often characterized as irreversible since a large proportion of these expenditures are directed toward the salaries of research personnel and the purchase of project-specific equipment and materials that cannot be recouped if projects fail. Czarnitzki and Toole (2011) provide evidence that firm R&D investment falls in response to a higher level of market uncertainty as the degree of uncertainty about returns to innovation increases. Bhattacharya et al. (2017) find that policy uncertainty adversely affects firms' innovation incentives and outcomes. Based on these arguments, it can be inferred that the high levels of uncertainty inherent in climate change may make firms less inclined to undertake irreversible investments, such as R&D.

Climate change also creates new risks to businesses, including systematic risks across the entire economy and specific risks at the industry and firm levels. These risks can be direct and indirect and categorized as i) physical risks, i.e., risks that arise from the physical impacts of climate change and extremes, such as supply-chain breakdowns, business disruptions, and loss of asset value; ii) transition risks, i.e., risks that stem from the transition to a low carbon economy, such as policy and technology changes and consumer demand shifts that disrupt business operations; iii) and other risks, such as financial risks (e.g., declined profitability and cash flows due to higher R&D costs and operating costs, increased liabilities), reputational risks, litigation risks, and strategic risks (as new industries emerge or old ones are transformed).[7]

These climate-related risks can affect how businesses operate, impact firm profitability, and accentuate the financial risks associated with innovation activities.[8] Hence, firms with a greater vulnerability to the risks and uncertainties related to climate change are likely to be more cautious and conservative about investing in R&D and innovation. Since climate vulnerability determines how severe climate change impacts might be, firms with a greater vulnerability are more exposed to climate hazards due to lower adaptive capacity to mitigate the potential damage.

Moreover, increasing climate risks may reduce firms' capabilities to innovate. First, innovative firms largely depend on infrastructure that facilitates innovation (e.g., Furman, Porter, and Stern, 2002). However, climate change and extreme weather can damage infrastructure directly and slow infrastructure development, both incurring higher costs of logistics in the supply chain. Second, as climate change has negative impacts on multi-dimensions of the workforce, including productivity, supply, effort, and migration (e.g., Black and Henderson, 1999; Graff Zivin and Neidell, 2014; Heal and Park, 2016), it may severely affect innovation process that requires specialized labor skills. Third, climate-related risks may impair firms' ability to finance R&D internally and externally. Huang, Kerstein, and Wang (2018) show that firms in countries with

[7] For example, hardware and semiconductor companies carry significant environmental risks. The wastewater generated from the production process contains high amounts of heavy metals and toxic chemicals, requiring higher operating costs and capital expenditures to deal with hazardous waste. Poor management of waste disposal can lead to significant regulatory fines and reputational damage.

[8] Innovation activities involve high financial risks due to a large amount of capital required and the uncertainty of innovation outcomes.

higher climate risks have significantly lower and more volatile earnings and cash flows. Jiang, Li, and Qian (2020) find that costs of corporate loans increase with sea-level rise risk. Also, the uncertainty due to a lack of information and financial expertise to assess the commercial viability of new green technologies makes external funding more expensive and less accessible. This could lead to underfunding and suboptimal levels of innovation. Fourth, climate-related policies and regulations (e.g., carbon taxes, cap and trade regimes, increased efficiency standards, mandates for renewable energy) call for more radical and disruptive technologies and make R&D more expensive.[9] Therefore, climate risks may increase the costs of R&D and lower a firm's capacity to engage in innovation, which will hurt innovation investment and performance.[10]

Climate-related uncertainties also worse the uncertain nature of innovation. Besides climate risks, the additional ambiguity about the future stringency, timing, nature, or durability of the climate policy framework affects the innovation activities.[11] The uncertainty in the cash flows due to climate risks (Huang, Kerstein, and Wang, 2018) also makes it difficult to evaluate the potential returns on R&D projects. In addition, climate vulnerability may indicate potential weaknesses or negatively affect competitiveness and market valuations, reducing the private economic value of innovations. With no guarantee to receive a reasonable return for R&D efforts, firms have lower incentives to innovate. Based on models of decision-making under uncertainty, it can be rational to delay irreversible investments (e.g., Pindyck, 1991; Dixit and Pindyck, 1994). Thus, in the face of unpredictability, firms with higher climate vulnerability are likely to forgo or postpone R&D

[9] For example, EVA Air reported that the company should use the latest energy conservation and carbon reduction technology to comply with environmental and energy laws and regulations, which increase its R&D costs (http://www.evacsr.com/FIle/en/EVA_CSR_2017.pdf).

[10] A firm's innovation capacity is an important determinant of innovation performance, as firms with greater innovation capacity are more productive in patenting and more likely to generate high-quality patents that could yield higher profits.

[11] Abadie, Chamorro, and González-Eguino (2013) point out that investments to enhance energy efficiency have huge potential but usually are not undertaken because of the numerous uncertainties that these investments face (e.g., regulatory framework, energy prices, or emission permit restrictions).

spending, monitor, and learn for more information before undertaking irreversible investments.

Following the above arguments, we posit that climate vulnerability reduces firms' incentives and capabilities to innovate and hinders innovation performance, which leads to the following testable hypothesis:

Hypothesis: firms with higher climate vulnerability have lower levels of R&D investment and innovation performance.

3. Data and summary statistics

3.1. Data and sample construction

We obtain the climate vulnerability index from the Notre Dame Global Adaptation Initiative (ND-GAIN). It is available for 182 countries from 1995 to the present and constructed based on 36 indicators.[12] This index measures a country's *exposure*, *sensitivity*, and *capacity* to adapt to the negative effects of climate change, thereby indicating a country's current vulnerability to climate disruptions. Specifically, the *exposure* captures the extent to which human society and its supporting sectors are stressed by the future changing climate conditions. The *sensitivity* measures the degree to which they are affected by climate hazards. The adaptive *capacity* reflects the ability to adjust to reduce potential damage and respond to the negative consequences of climate change. According to ND-GAIN, the index and underlying data are widely used by corporations, NGOs, governments, and development decision-makers to make informed strategic and operational decisions regarding capital projects, supply chains, policy changes, and community engagements.

[12] The construction of the index is based on published peer-reviewed material, the IPCC Review process, and feedback from corporate stakeholders, practitioners, and development users. Note that GDP per capita or any of its closely related measures is explicitly excluded from the ND-GAIN index. Because GDP per capita is commonly used in indices relating to development and poverty (e.g., Human Development Index), including it in ND-GAIN would doubly penalize many developing countries.

To gauge firms' innovation activities, we extract R&D expenses and financial information from Compustat North America and Global Fundamentals annual databases. We also use global firm-level patent data from the UVA Darden Global Corporate Patent Dataset and the extended patent dataset of Kogan, Papanikolaou, Seru, and Stoffman (2017).[13] The Global Corporate Patent Dataset is based on Bena, Ferreira, Matos, and Pires (2017) and includes patents granted by the USPTO to publicly listed firms worldwide, covered by Compustat North America or Compustat Global databases. Kogan et al. (2017) focus on USPTO granted patents to U.S. listed firms, including those with headquarters located in other countries. The combination of the two datasets provides comprehensive data on patenting by international firms.

Bena et al. (2017) argue that using USPTO patents to measure innovation output in the international setting has several advantages. First, it avoids the difficulty to aggregate patent statistics across different patent offices and over time, as patent regulations and patent office practices across countries may not be comparable. Second, it alleviates the concern that there exists excessive heterogeneity in the quality of patents. For non-U.S. firms, the patents filed to the USPTO arguably reflect more important innovations, making the filers more willing to pay the costs of securing a patent in the U.S. In fact, USPTO has granted more patents to non-U.S. firms than U.S. firms in recent years. Last, using USPTO patents does not necessarily underestimate innovation output because the dataset contains predominantly large firms that commonly protect their innovations by filing patents at the USPTO and the European and Japanese Patent Offices (EPO and JPO) simultaneously, irrespective of domicile. Therefore, by using USPTO patents, we ensure the consistency and comparability of the quality, economic value, application procedure,

[13] The Global Corporate Patent Dataset is developed by the Batten Institute for Entrepreneurship and Innovation at the University of Virginia Darden School of Business and can be downloaded from https://patents.darden.virginia.edu/. KPSS (2017) patent data can be accessed through https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

and legal protection of patent across different economies (e.g., Jaffe and Trajtenberg, 2002; Lerner, 2009; Bhattacharya et al., 2017).

Our initial sample consists of a panel of publicly listed firms drawn from the Compustat North America and Compustat Global databases. After merging with the climate vulnerability index data and patent data, the final sample consists of 743,870 firm-year observations for 60,028 unique firms from 88 countries during 1995-2019.

3.2. Variable measurement

The key explanatory variable of interest *Vulnerability* is the climate vulnerability index of country j in year t, which captures a country's current vulnerability to climate disruptions. Our main dependent variable is the R&D investment of firm i in country j in year t+1 ($R\&D_{i,j,t+1}$), defined as R&D expenses scaled by total assets in year t+1, which measures a firm's innovation input. We follow the innovation literature and set the missing R&D expenses to zero. We also construct two proxies for innovation output. The first one is the number of successful patent applications, often known as "patent count," which is widely used to measure the quantity of innovation (e.g., Kamien and Schwartz, 1975; Griliches, 1990). The second one is the number of patent citations, which accounts for the quality of innovation, as citations are more reflective of a patent's technological and economic significance or scientific value (Trajtenberg, 1990; Harhoff, Narin, Scherer, and Vopel, 1999; Hall, Jaffe, and Trajtenberg, 2005; Aghion, Van Reenen, and Zingales, 2013; Kogan et al., 2017).

We count patents as of the filing date, which is the time that is closest to when the innovation was created. Following the innovation literature (e.g., Atanassov, 2013; Cornaggia, Mao, Tian, and Wolfe, 2015; Bena et al., 2017), we set the number of patents to zero for firm-years with no patent information available. As the distributions of patents and citations are highly skewed, we use the natural logarithm of one plus the number of successful patent applications or the number of citations received by these patents of firm *i* in country *j* in year *t*+1 ($LnPatents_{i,j,t+1}$ and $LnCitations_{i,j,t+1}$) in our regressions. Because there is a significant time lag (about two years on average) between a patent's application year and its grant year, we also calculate $LnPatents_{i,j,t+1, t+3}$ and $LnCitations_{i,j,t+1, t+3}$ over the three years from *t*+1 to *t*+3 to address the truncation problem. In robustness checks, we also use a shorter sample period of 1995-2017 and find consistent results.

3.3. Summary statistics

Panel A of Table 1 shows that the average climate vulnerability index ranges from 0.265 (Norway) to 0.611 (Sudan). A higher value of the vulnerability index indicates the more severe impacts of climate change. The U.S. firms have the highest total amount of R&D expenditures, followed by Japan and Germany. Our sample firms were granted a total of 2,446,032 patents by the USPTO over the period 1996-2019. The distribution of patents across countries illustrates the global nature of innovation. More than half of the patents are granted to non-U.S. firms. The U.S. firms have the highest total number of USPTO patents, followed by Japan and South Korea.[14]

Panel B of Table 1 reports that descriptive statistics across all firm-year observations in our sample. To mitigate the influence of outliers, we winsorize firm-level continuous variables at the 1st and 99th percentiles. Our sample firms have an average R&D investment ($R\&D_{t+1}$) of 0.015 with a standard deviation of 0.051 and an average climate vulnerability index (*Vulnerability*) of 0.380 with a standard deviation of 0.066. The mean of patents and citations ($LnPatents_{t+1}$ and $LnCitations_{t+1}$) are 0.131 and 0.187, respectively. The average firm size (*Size*) is 5.017. In Internet

[14] In the robustness check, we exclude U.S. firms and find qualitatively similar results.

Appendix Table IA1, we present the average cross-country time-series correlations of our main variables.

[TABLE 1 ABOUT HERE]

3.4. Empirical test specification

To test the effects of climate vulnerability on firms' R&D investment and innovation performance, we estimate the following ordinary least squares (OLS) regressions:

$$R\&D_{i,j,t+1} = \beta_0 + \beta_1\, Vulnerability_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t+1}, \tag{1}$$

$$LnPatents_{i,j,t+1},\ LnCitations_{i,j,t+1},\ LnPatents_{i,j,t+1,t+3},\ \text{or}\ LnCitations_{i,j,t+1,t+3} = \beta_0 + \beta_1\, Vulnerability_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t+1}, \tag{2}$$

where subscript *i* indexes firms, *j* indexes countries, and *t* indexes years. The dependent variables are defined in Section 3.2. *Vulnerability* is the climate vulnerability of country *j* in year *t*.

The vector *X* includes a set of firm-specific control variables as well as country-level factors measured in year *t*, including firm size, market-to-book ratio, tangibility, cash holdings, free cash flow, leverage ratio, return on assets, GDP per capita, GDP growth, political stability, policy uncertainty, property rights, the development of credit market and equity market, and Human Development Index, as well as capital expenditures and lagged R&D intensity for Equation (2) (detailed variable definitions are provided in the Appendix).

We include firm and year fixed effects in all regressions. Firm fixed effects account for unobserved time-invariant firm heterogeneity, such as corporate innovation culture or the risk of sea level rise. The inclusion of year fixed effects controls for variation over time in innovation activities (or a potential time trend effect) and any year-specific factors that may confound our findings. As time-invariant measures have no explanatory power in a firm fixed effects framework (e.g., McLean, Zhang, and Zhao, 2012), industry and country fixed effects are irrelevant in a framework with firm fixed effects and therefore are not included in our regressions. In the robustness checks, we use alternative sets of fixed effects such as country, industry, and year fixed effects, or country-industry and industry-year joint fixed effects, and obtain qualitatively similar results.

4. Empirical results

4.1. Baseline results

Table 2 reports the estimation results of Equation (1). We show that climate vulnerability (*Vulnerability*) in year t is significantly and negatively associated with firms' R&D investment in year t+1. In terms of economic magnitude, the coefficient on *Vulnerability* of −0.109 in column 4 suggests that a one-standard-deviation increase in climate vulnerability is associated with a 0.72 percentage points decrease (−0.066×0.109) in R&D investment, which corresponds to a 48% decrease relative to the mean of R&D-to-assets ratio, or a 14.1% decrease relative to the standard deviation. The result provides strong support for our hypothesis. It is also consistent with prior findings that in the face of greater uncertainty and risk, firms are more cautious and reluctant to invest in R&D and innovation (e.g., Bloom, 2007; Czarnitzki and Toole, 2011; Bhattacharya, Hsu, Tian, and Xu, 2017).

[TABLE 2 ABOUT HERE]

In Table 3, we examine how climate vulnerability affects technological innovation success, as measured by patent counts and citation counts. The dependent variables are $LnPatents_{i,j,t+1}$, $LnPatents_{i,j,t+1,t+3}$, $Ln\text{Citations}_{i,j,t+1}$, and $Ln\text{Citations}_{i,j,t+1,t+3}$ from columns 1 to 4, respectively. We find a significant negative effect of climate vulnerability on firm innovation output. For example, in column 1, the coefficient on *Vulnerability* is −5.511 and statistically significant at the 1% level. This result suggests that a one-standard-deviation increase in climate vulnerability leads to a decrease of nearly 36% (−0.066×5.511) in the number of patents. The result indicates that climate vulnerability adversely affects firm innovation performance. Collectively, our evidence suggests that climate vulnerability hinders corporate innovation activities.

[TABLE 3 ABOUT HERE]

4.2. Potential channels

In this section, we discuss the potential economic channels through which climate vulnerability impedes corporate innovation, including investment efficiency, incentives to innovate, and the private economic value of new innovations.

4.2.1. Sensitivity of R&D to investment opportunities

The conventional models of investment under uncertainty predict that when investment decisions are irreversible or just even partially irreversible, firms become more cautious and hold back on investment in the face of uncertainty (e.g., Pindyck, 1991; Dixit and Pindyck, 1994; Czarnitzki and Toole, 2011; Gulen and Ion, 2016). As a result, higher uncertainty leads to a reduction in firms' responsiveness to the investment opportunity set (e.g., Bloom et al., 2007; Julio and Yook, 2012). In line with this, Wellman (2017) shows that uncertainty causes managers to forgo investment, potentially shifting opportunities toward firms that can better mitigate the effects of uncertainty. Based on these studies, we conjecture that climate-related uncertainties may affect the optimal allocation of R&D capital since R&D investment has a high degree of irreversibility and a long time horizon with uncertain payoffs.

Following prior studies (e.g., Badertscher, Shroff, and White, 2013; Zhong, 2018), we use the responsiveness of R&D investment to investment opportunities (*Tobin's Q*) as a proxy for investment efficiency and examine how it varies with climate vulnerability as follows:

$$R\&D_{i,j,t+1} = \beta_0 + \beta_1\, Tobin's\ Q_{i,j,t} \times Vulnerability_{j,t} + \beta_2\, Tobin's\ Q_{i,j,t} + \beta_3\, Vulnerability_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t+1}. \tag{3}$$

Tobin's Q is calculated as (total assets + market value of equity – book value of equity – deferred taxes) divided by total assets in year *t*. It captures the market's information about investment opportunities (Hubbard, 1998; Stein, 2003). In Table 4, the coefficients on *Tobin's Q ×Vulnerability* are significantly negative, and the coefficients on *Tobin's Q* are significantly positive. The result is consistent with our conjecture that climate vulnerability substantially decreases the responsiveness of R&D investment to the investment opportunity set. Climate vulnerability causes firms to forgo some investment opportunities (i.e., to be less willing to take great risks), which results in lower investment efficiency.

[TABLE 4 ABOUT HERE]

4.2.2. Incentives to innovate

We next investigate the extent to which climate vulnerability impacts firms' incentives to innovate. As discussed in Section 2, climate-related risks and uncertainties (e.g., physical risks, transition risks, financial risks, lack of certainty about climate policies, rising future costs, unexpected costs arising from future policy shifts) can increase the costs, risks, and uncertainties of R&D and innovation. We thus expect a negative relation between climate vulnerability and firms' incentives to innovate.

Bhattacharya et al. (2017) use the numbers of patent inventors that have filed at least one patent in a sample country-industry-year as a proxy for incentives to innovate. The rationale is that given the stable population size across years, more inventors filing patent applications reflect a stronger incentive to innovate. Following their methodology, we estimate the following regression:

$$LnInventors_{k,j,t+1} = \beta_0 + \beta_1\, Vulnerability_{j,t} + \delta' X + Country\text{-}industry\ FE + Year\ FE + \varepsilon_{k,j,t+1}, \quad (4)$$

where the dependent variable $LnInventors_{k,j,t+1}$ is the natural logarithm of one plus the number of patent assignees who have ever filed at least one patent of industry k of country j in year t+1. *Vulnerability* is country j's vulnerability to climate disruptions in year t. The vector X includes a set of country-level factors measured in year t as well as the lagged number of inventors ($LnInventors_{k,j,t}$). We include country-industry fixed effects to capture any factors associated with specific industries in certain countries as well as year fixed effects.

In Table 5, we find that the inventors' incentive to innovate is reduced by climate vulnerability. As shown in all columns, the coefficients of *Vulnerability* are negative and significant, indicating that innovation incentives, proxied by the number of inventors filing patents, decline significantly with climate vulnerability. This finding supports our interpretation that climate vulnerability lowers the incentives to engage in innovation activities, contributing to the lower R&D investment and fewer innovations.

[TABLE 5 ABOUT HERE]

4.2.3. Patent grant announcement returns and patent value

Recent studies suggest that climate change risks have significant negative impacts on asset valuations (e.g., Hong, Li, and Xu, 2019; Baldauf, Garlappi, and Yannelis, 2020; Hong, Karolyi, and Scheinkman, 2020). In particular, Bansal, Kiku, and Ochoa (2019) find that a one-standard-deviation increase in the temperature trend leads to about a 3% decline in equity valuations. Hence, equity prices reflect investors' concern about the impact of rising temperature on long-run economic growth and risk. Since the market value of patents and R&D are positively associated with firm valuation (e.g., Bloom and Van Reenen, 2002; Hall et al., 2005), the economic value of new innovations may also be affected by climate impacts. Besides, climate-related risks can increase R&D costs, reduce firms' innovation capabilities, and cause economic, policy, technology, market, consumer demand, and social changes. These shocks may lower the private return to R&D spending, impair production of high-quality patents, and reduce the prospect of successful patent commercialization on which patent value depends.

Similar to Kogan et al. (2017) and Custódio et al. (2019), we run an event study using a global sample of patent grant announcements and estimate cumulative abnormal returns (CAR) over the three-day event window (0, +2) around the patent grant announcement date. We divide the sample by the yearly median of the climate vulnerability index, yielding a high vulnerability group of 1,211,738 patents and a low vulnerability group of 1,647,912 patents. We then calculate the mean and median CARs for each group. Both raw returns and market-adjusted returns are calculated using stock returns data from CRSP and Compustat Global-Security Daily databases. For market-adjusted returns, the raw returns are adjusted by the CRSP value-weighted market returns or the country total return indices from World Indices by WRDS database.

[TABLE 6 ABOUT HERE]

Panel A of Table 6 shows that the average raw returns and market-adjusted returns of new patents filed by firms with high climate vulnerability are 18.8 and 2.7 basis points per patent, respectively. The returns are significantly lower than those of the low climate vulnerability group (22.7 and 6.2 basis points per patent). Using median returns yields similar results. This finding indicates that climate vulnerability weakens the contribution of innovation to firm valuation.

Further, we follow prior research (e.g., Kogan et al., 2017; Brav, Jiang, Ma, and Tian, 2018) and measure the private economic value of new innovations using the market value of a new patent implied by the market responses to the patent approval. Specifically, a patent's market value is calculated as the firm's stock return in excess of the market over the three-day window (0, +2) around the date of patent approval, multiplied by the firm's market capitalization on the day prior to the announcement. We then regress the market value of new patents (in ten million U.S. dollars) on climate vulnerability and find significant negative coefficients on *Vulnerability*, as reported in Panel B of Table 6. The result indicates that climate vulnerability reduces the private economic value of new patents. These findings provide supportive evidence for the lower incentives to innovate for firms with greater vulnerability to climate change.

In sum, this section shows that climate vulnerability impedes corporate innovation activities by reducing investment efficiency (the responsiveness of R&D investment to investment opportunities), lowering incentives to innovate, and decreasing private returns to innovation. Consequently, firms that are more vulnerable to climate change tend to have lower R&D investment and innovation output.

5. Subsample tests, climate-related natural disasters, and robustness checks

In this section, we first explore the relation between climate vulnerability and R&D investment using subsamples of long/short product development cycles, high/low attention to climate change, and developing/developed countries. We then address possible endogeneity concerns by conducting a difference-in-differences (DID) analysis based on climate-related natural disasters. Finally, we perform various robustness checks.

5.1. Subsample tests

Managers are under pressure to deliver short-term results at the expense of long-term sustainable performance such that they could meet short-term earnings targets. The 2019 Deloitte European CFO Survey of 1,168 CFOs reveals that most companies' climate responses focus primarily on measures that have a short-term cost-saving effect, and few companies have a governance and steering mechanism in place to develop and implement comprehensive climate strategies. A long product development cycle may increase managers' career risk because managers typically have limited career horizons, while the returns to R&D investment take time to realize. Hence, firms that are highly vulnerable to the physical or economic transition risks associated with climate change may be less inclined to invest in R&D, especially for those with a long product development cycle.

Following Zhang (2018), we measure the product development cycle as the industry-level R&D amortizable life because products with longer development cycles generally have longer amortizable lives. We then divide the sample of Table 2 into high and low groups by the median of the product development cycle and re-estimate Equation (1) for each subsample. Consistent with our expectation, we find that the negative effect of climate vulnerability on R&D investment is more pronounced for firms with longer product development cycles. As reported in columns 1 and 2 of Table 7, the coefficients of *Vulnerability* are significantly more negative for firms with longer product development cycles when managers face greater ex-ante career risks of investing in R&D.

[TABLE 7 ABOUT HERE]

Choi, Gao, and Jiang (2020) show that people experiencing abnormally warm weather pay more attention to climate change, as measured by the monthly Google Search Volume Index (SVI) of the topic "global warming" in a city. Similarly, Sautner et al. (2020) find a strong positive association between the time-series variation in media attention to climate change and the firm-level exposures to regulatory and physical climate shocks. Thus, we expect the negative effect of climate vulnerability on R&D investment to be larger among firms with more attention to climate change.

We use the Google SVI of the topic "Climate variability and change" in each country as a measure for attention on climate change.[15] Google divides each data point by the total searches of the geography and time range it represents to compare relative popularity. The resulting numbers are scaled between 0 to 100 based on a topic's proportion to searches on all topics. We thus classify our sample into high and low attention groups by the median of Google SVI within each country. Columns 3 and 4 of Table 7 show that the negative effect of climate vulnerability on R&D is significantly stronger among firms with more attention to climate change. The result indicates that firms with more severe climate impacts (i.e., those with greater climate vulnerability) and greater attention to climate change tend to be more conservative in investing in R&D.

[15] Google provides SVI for topics and search terms. Similar to Choi, Gao, and Jiang (2020), we use topics instead of search terms because the former addresses misspellings and searches in different languages, as Google's algorithms can group different searches that have the same meaning under a single topic. Our Google data capture the search activity on the topic "Climate variability and change" in each country and cover different languages.

In addition, we also estimate Equation (1) for developed and developing countries separately. The coefficient of *Vulnerability* is −0.087 and statistically significant at the 5% level for developed countries and −0.024 and statistically significant at the 1% level for developing countries. The results suggest that our main finding is not solely driven by developing countries that are likely to be more vulnerable to climate change due to their lower adaptive capacity.

5.2. Innovation strategies

Climate change also brings new business opportunities. Under the stress of transition risks associated with climate change, companies feel the need to improve resource allocation efficiency and implement sustainable manufacturing practices, such as minimizing waste, recycling materials, shifting towards renewable energy, reducing greenhouse gases emission, and developing sustainable technologies and green products/services. Motivated by economic incentives (e.g., carbon taxes and cap and trade regimes) and legal initiatives, research and investments in Climate Change Mitigation Technologies (CCMTs) have grown tremendously over the years. For example, European companies have invested about 250 €bn in R&D activities concerning CCMTs from 2003 to 2014 (Pasimeni, Fiorini, and Georgakaki, 2019). Given the critical role of CCMTs, firms with high climate vulnerability are likely to engage in technology development for mitigating or adapting to climate change.

To test this conjecture, we follow prior studies (e.g., Veefkind et al., 2012; Angelucci, Hurtado-Albir, and Volpe, 2018; Pasimeni et al., 2019) and classify "CCMT patents" based on Cooperative Patent Classification (CPC) of Y02 or Y04S.[16] Specifically, Y02 covers technologies that control, reduce, or prevent greenhouse gas emissions and technologies that allow adaptation

[16] The detailed description of CPC can be found at https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html#Y02.

to the adverse effects of climate change. Y04S includes systems integrating technologies related to power network operation, communication, or information technologies (i.e., smart grids). We then regress the *CCMT ratio*, defined as the ratio of CCMT patents in the total number of patents filed by firm *i* over years *t*+1 to *t*+3, on climate vulnerability in year *t*. Column 1 of Table 8 shows that the coefficient of *Vulnerability* is 0.323 and statistically significant at the 5% level. The result indicates that climate vulnerability increases the ratio of CCMT patents in new innovations. Although climate vulnerability negatively impacts overall corporate innovation, firms in countries with high climate vulnerability indeed invest more in CCMTs that might mitigate the adversity.

The literature (e.g., March, 1991; Manso, 2011; Custódio et al., 2019) also identifies two essential innovative strategies: exploitative and exploratory. The exploitative strategy refines or extends existing technologies. In contrast, the exploratory strategy requires new knowledge or departures from existing knowledge and involves the experimentation with new alternatives that are associated with uncertain, distant, and often negative returns. Since the exploratory strategy involves disruptive changes and path-breaking and is riskier, firms with high climate vulnerability may be more likely to engage in less risky exploitative strategies.

Following prior studies (e.g., Custódio et al., 2019), we categorize a patent as exploitative if at least 60% of its citations are based on the firm's existing knowledge and as exploratory if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge set).[17] We find that climate vulnerability has a negative effect on the *Exploratory ratio* but a positive effect on the *Exploitative ratio*, as shown in columns 2 and 3 in Table 8. The result suggests that firms with greater climate vulnerability tend to pursue more conservative innovation

[17] Alternatively, similar to Brav, Jiang, Ma, and Tian (2018), we define a patent as exploitative if at least 80% of its citations are based on the firm's existing knowledge and as exploratory if at least 80% of its citations are based on new knowledge. Untabulated results are qualitatively similar.

strategies and engage more in exploitative than exploratory innovations.

[TABLE 8 ABOUT HERE]

In addition, we show that climate vulnerability negatively affects the absolute number of patents associated with different innovation strategies, including non-CCMT patents, CCMT patents, exploratory patents, and exploitative patents. As reported in Table IA2, the coefficients on *Vulnerability* are significantly negative in all the columns. For non-CCMT patents and exploratory patents, the negative effect of climate vulnerability is much stronger. These results collectively show that climate vulnerability nudges firms to pursue innovation in climate change mitigation/adaptation technologies, which leads to an increase in the ratio of CCMT patents in new innovations. However, the absolute number of CCMT patents still decreases. This result is consistent with Gans (2012) that climate change policy may stimulate the relative demand for innovations that improve energy efficiency. But it also diminishes innovation incentives overall as it increases the overall scarcity of factors in the economy (at least in the short run) and possibly because investments under uncertain climate policy tend to be much riskier as well (e.g., Abadie, Chamorro, and González-Eguino, 2013).

5.3. Difference-in-differences regressions based on natural disasters

Climate change and extreme weather events are most likely to be exogenous to a firm's innovation activities.[18] Nevertheless, we use a difference-in-differences (DID) regression analysis based on climate-related natural disasters to better identify the causal effect of climate change on R&D investment. The events we focus on include the 2003 heatwave in France, the 2003 European

[18] However, there is a possibility that when firms pursue more innovation for mitigating or adapting to climate change, climate vulnerability may reduce. Abdelzaher, Martynov, and Zaher (2020) examine the impact of a country's degree of innovation on its vulnerability to climate change and find that a country's R&D expenditures as a percentage of GDP decrease a country's vulnerability to climate change based on country-level data over 1998-2013.

heatwave, the 2004 Asian tsunami, the 2011 Japan's earthquake and tsunami, and the 2011 Thailand's flooding, which caused severe casualties and economic losses. The most affected countries by the 2003 European heatwave include France, Germany, Spain, Italy, UK, Netherlands, Portugal, Belgium, Switzerland, Austria, Finland, Denmark, and Ireland. The six most-affected countries in the 2004 Asian tsunami in our sample are Indonesia, Sri Lanka, India, Thailand, Malaysia, and Tanzania.

For each event, we estimate the following DID regression using an event window of (t−3, t+3) around the natural disaster year:

$$R\&D_{i,j,t} = \beta_0 + \beta_1\, Treat_j \times Post_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t}, \tag{5}$$

where the dependent variable $R\&D_{i,j,t}$ is the R&D investment of firm i in country j in year t. $Treat_j$ is a dummy equal to one for the treated country j and zero otherwise. $Post_{j,t}$ is a dummy that equals one for post-disaster years and zero otherwise. The vector X includes the same control variables as in Equation (1). We include firm and year fixed effects. *Treat* and *Post* dummies are omitted due to collinearity with the fixed effects.

In Table 9, columns 1, 3, 5, 7, and 9 use all other countries as the control groups, while columns 2, 4, 6, 8, and 10 only use the treated country (or countries). The coefficients on *Treat* × *Post* are significantly negative in all the columns, suggesting that firms in treated countries invest significantly less in R&D after the natural disaster events. This evidence supports our causal interpretation that climate-related risks adversely impact firms' R&D investment.

[TABLE 9 ABOUT HERE]

5.4. Robustness checks

We perform a battery of robustness tests for our main findings. To begin with, we use the firm-level measures of climate change exposure constructed by Sautner, van Lent, Vilkov, and Zhang (2020). They adopt a machine learning keyword discovery algorithm to produce a set of climate change bigrams and identify firm-level climate change exposure from transcripts of quarterly earnings conference calls of more than 10,000 firms from 34 countries over 2002-2019. The measure of climate change exposure (*CCExposure*) is based on the frequency of climate change bigrams in a given transcript, scaled by the total number of bigrams in the transcript. The measure of climate change risk (*CCRisk*) is constructed by counting the relative frequency of climate change bigrams mentioned in the same sentence with the words "risk" or "uncertainty" (or their synonyms). In Table 10, we find significant negative effects of *CCExposure* and *CCRisk* on R&D investment and innovation output, consistent with our hypothesis.[19]

[TABLE 10 ABOUT HERE]

We further use the Climate Risk Index (CRI) annually published by the Germanwatch to measure climate risk in a country. It analyses the quantified impacts of extreme weather events by country both in terms of economic losses and fatalities. It also indicates the level of exposure and vulnerability to extreme events in the future. The CRI has been published annually since 2006 and contains two sets of scores: annual and long-term. We adopt annual scores for the years 2004-2018 and long-term scores for years before 2004. Since lower CRI scores indicate higher climate risk, we multiply the index by −1 so that higher values of the index now represent greater climate risk.

[19] Sautner, van Lent, Vilkov, and Zhang (2020) find that between 70.4 and 96.8% of the variation in their climate exposure measures plays out at the firm level and half of this firm-level variation is persistent. They mention that exposure to physical shocks is highly dependent on firm-specifics (e.g., the location of a firm's headquarters, production sites, the supply chain specifics, and its specific insurance policies). Following their paper, we use country, industry, and year fixed effects in the regressions for Table 10.

Panel A of Internet Appendix Table IA3 shows that firm-level R&D investment and innovation performance are significantly negatively affected by country-level CRI.

Panel B of Table IA3 reports the results using the Notre Dame-Global Adaptation Index. This index assesses both a country's current vulnerability to climate disruptions and also a country's readiness to leverage private and public sector investment for adaptive actions. It is computed by subtracting the vulnerability score from the readiness score for each country and scaled to yield a value between 0 and 100 (i.e., ND-GAIN score = (readiness score − vulnerability score +1) × 50). We find significant positive associations between the ND-GAIN score and firm-level R&D investment and innovation performance, suggesting that climate adaptation readiness (e.g., economic, governance, and social readiness) fosters firm innovation activities and mitigates the negative effect of climate vulnerability.

In Panel A of Table IA4, we re-estimate Equations (1) and (2) using alternative measures of firm innovation activities: (i) $R\&D_{i,j,t+2}$ and $R\&D_{i,j,t+3}$, calculated as the R&D expenses scaled by total assets of firm i in country j in year t+2 or t+3; (ii) R&D growth of firm i in country j in year t+1 ($R\&D\ growth_{t+1}$), defined as $ln(1 + R\&D_{i,j,t+1}) – ln(1 + R\&D_{i,j,t})$; (iii) the natural logarithm of one plus the number of patent applications or citations received by patents filed by firm i in country j in year t+2 or t+3; (iv) innovation growth of firm i in country j in year t+1 ($Patent\ growth_{t+1}$), defined as $ln(1 + Patent_{i,j,t+1}) – ln(1 + Patent_{i,j,t})$. Panel B uses alternative fixed effects, including country, industry, year, country-industry, or industry-year fixed effects. All the results remain consistent. Finally, as reported in Table IA5, our main results hold for the subsamples of non-U.S. firms, firms with at least one patent application during our sample period, and the period of 1995-2017 for addressing the truncation issue due to the patent application-grant lag.

6. Conclusion

We provide novel evidence that the vulnerability to climate change adversely affects firms' R&D investment and innovation performance across the world based on a sample of 60,028 firms from 88 countries during the period 1995-2019. We show that this effect operates through (i) the decreased responsiveness of R&D investment to investment opportunities, which leads to inefficient allocation of R&D capital and lower investment efficiency; (ii) the reduced incentives to innovate; and (iii) the lower private economic value of new innovations. Through these channels, climate vulnerability hinders corporate innovation activities.

Our subsample results show that the negative effect of climate vulnerability on R&D investment is more pronounced for firms with longer product development cycles and more attention to climate change. The effect exists not only in developing countries but also in developed ones. Moreover, we find that climate vulnerability increases the ratio of patents on climate change mitigation technologies in new innovations and triggers more exploitative innovations. We provide the causal inference by using a DiD analysis based on climate-related natural disasters. Our findings are also corroborated by alternative measures of climate change exposure at both firm and country levels.

Overall, our study offers a new perspective on the mechanisms through which climate change adversely affects economic growth. Our findings provide practical implications for companies, policymakers, and regulators. Building capacities to cope with climate change uncertainty is a key action for adaptation. It is also essential to increase in-house capacity and expertise in companies that enable them to assess climate risks and implement adaptation actions more efficiently. Governments are suggested to reduce uncertainties associated with climate policies and regulations where possible and provide more support (e.g., subsidy, long-term climate policy framework) to increase firms’ incentives and capabilities to innovate.

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Appendix. Variable Definitions

Variable	Definition
R&D$_{t+1}$	R&D expense divided by the total assets in year *t*+1, *xrd/at*, *xrd* is set to 0 if missing. Source: Compustat global and North America
LnPatents$_{t+1}$	The natural logarithm of one plus the number of successful patent applications filed by firm *i* in country *j* in year *t*+1 (and granted by the end of 2019).
LnCitations$_{t+1}$	The natural logarithm of one plus the total number of forward citations received by patents filed by firm *i* in country *j* in year *t*+1.
Vulnerability	A country's vulnerability to climate disruptions in year *t*. The climate vulnerability index is a sub-index of the Notre Dame-Global Adaptation Index (ND-GAIN). The ND-GAIN index is compiled and published by the University of Notre Dame, a time-series index for assessing the impact of climate change since 1995 (https://gain.nd.edu/our-work/country-index/).
Size	The natural logarithm of the book value of total assets (in million U.S dollars), *at*.
M/B	Market value of equity divided by book value of equity, *mv/ ceq*. *mv* is calculated as stock price times share outstanding at the end of the fiscal year (*csho*×*prcc_f*).
Tobin's Q	Tobin's Q is calculated as (Book value of total assets + market value of equity – book value of equity – deferred taxes) divided by the book value of total assets, similar to Gompers, Ishii, and Metrick (2003). Compustat: (*at*+ *csho*×*prcc_f* − ceq – txdb)/at.
Tangibility	The ratio of total tangible assets (i.e., property, plant and equipment) to book value of total assets, *ppent/at.*
Cash	Cash holdings, calculated as cash and short-term investments divided by total assets, *che/at*.
Free cash flow	Cash flow to total assets, *(oibdp−xint−txt−dvc)/at*.
Leverage	Total debt divided by total assets, *(dltt+dlc)/at*.
ROA	Return on assets, *oibdp/at*.
Capex	Capital expenditures to total assets, *capx/at*.
LnGDPpcap	The natural logarithm of GDP per capita (current US$). Source: The World Bank DataBank (https://data.worldbank.org/indicator/NY.GDP.PCAP.CD)
GDP growth	GDP growth (annual %). It is divided by 100 in regressions. Source: The World Bank DataBank (https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG).
Political stability	The index of political stability and absence of violence (http://info.worldbank.org/governance/wgi/).
Uncertainty	The World Uncertainty Index (WUI) uses frequency counts of "uncertainty" (and its variants) in the quarterly Economist Intelligence Unit (EIU) country reports. The EIU reports discuss major political and economic developments in each country, along with analysis and forecasts of political, policy and economic conditions. To make the WUI comparable across countries, the raw counts are scaled by the total number of words in each report (https://www.policyuncertainty.com/wui_quarterly.html).
Property rights	A rating of property rights in each country, which provides a quantifiable measure of the degree to which a country's laws protect private property rights and the extent to which those laws are respected. It is divided by 100 in regressions. Source: The Index of Economic Freedom from Heritage Foundation (https://www.heritage.org/index/explore).
Credit market	Domestic credit to private sector (% of GDP). It is divided by 100 in regressions. Source: The World Bank DataBank (https://data.worldbank.org/indicator/FS.AST.PRVT.GD.ZS).
Equity market	Market capitalization of listed domestic companies (% of GDP). It is divided by 100 in regressions. Source: The World Bank DataBank (https://data.worldbank.org/indicator/CM.MKT.LCAP.GD.ZS).
HDI	Human development index. Source: United Nations Development Programme Human Development Data Center (http://hdr.undp.org/en/data, http://hdr.undp.org/en/content/human-development-index-hdi).
CCMT ratio	A patent is classified as climate change mitigation technologies (CCMTs) if its Cooperative Patent Classification (CPC) is Y02 or Y04S. *CCMT ratio* is defined as the number of CCMT patents filed by firm *i* in country *j* over years *t*+1 to *t*+3 divided by the total number of patents filed by firm *i* over years *t*+1 to *t*+3.
Product development cycle	It is measured as the industry-level R&D amortizable life, similar to Zhong (2018). Source: Aswath Damodaran's website: http://people.stern.nyu.edu/adamodar/New_Home_Page/spreadsh.htm

Exploitative Ratio	The number of exploitative patents filed by firm *i* in country *j* over years *t*+1 to *t*+3 divided by the number of all patents filed by firm *i* in country *j* over years *t*+1 to *t*+3. A patent is categorized as exploitative if at least 60% of its citations are based on the firm's existing knowledge.
Exploratory Ratio	The number of exploratory patents filed by firm *i* in country *j* over years *t*+1 to *t*+3 divided by the number of all patents filed by firm *i* in country *j* over years *t*+1 to *t*+3. A patent is categorized as exploratory if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge).

Table 1
Summary statistics

The sample consists of 743,870 firm-year observations for 60,028 unique firms from 88 countries during 1995-2019. Panel A shows the statistics on climate vulnerability, research and development (R&D) expenditures, number of patents filed with the USPTO, and the number of publicly listed firms by country. *Mean Vulnerability* is the average of a country's vulnerability to climate disruptions in year *t*. *Total R&D* (in billion U.S. dollars) is the total R&D expenditures in year *t*+1 across all firms during 1995-2019. *Mean R&D/Assets* is the average of a firm's R&D expense scaled by total assets in year *t*+1. *Total patents* (*Mean patents*) is the total (average) number of successful patent applications filed by all firms in year *t*+1 (and granted by 2019) during the sample period. Panel B reports descriptive statistics at the firm-level based on all firm-year observations. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. All variables are defined in the Appendix.

Panel A: Descriptive statistics by country

Country	Mean Vulnerability	Total R&D ($billion)	Mean R&D/Assets	Total patents	Mean patents	Number of firms
Argentina	0.405	1.327	0.001	15	0.009	109
Australia	0.338	43.288	0.035	1,059	0.029	3,020
Austria	0.296	20.754	0.012	742	0.328	183
Bahamas	0.464	0.096	0.833	21	0.344	5
Bangladesh	0.567	0.056	0.000	0	0.000	309
Belgium	0.364	53.748	0.023	2,006	0.602	261
Botswana	0.480	0.000	0.000	0	0.000	26
Brazil	0.410	39.815	0.001	505	0.063	541
Bulgaria	0.365	0.025	0.000	0	0.000	100
Canada	0.315	85.754	0.046	18,530	4.453	534
Chile	0.357	0.910	0.000	1	0.000	260
China	0.413	693.801	0.010	8,267	0.131	4,987
Colombia	0.423	0.179	0.000	5	0.005	71
Costa Rica	0.385	0.015	0.129	0	0.000	1
Cote d'Ivoire	0.512	0.000	0.000	0	0.000	28
Croatia	0.395	82.584	0.005	0	0.000	102
Cyprus	0.356	0.175	0.000	0	0.000	109
Czech Republic	0.308	0.984	0.001	0	0.000	54
Denmark	0.331	76.036	0.031	4,006	0.949	341
Egypt	0.447	0.048	0.000	0	0.000	220
Estonia	0.364	0.083	0.001	0	0.000	26
Finland	0.298	142.085	0.033	19,168	5.821	241
France	0.309	623.611	0.023	34,657	2.072	1,415
Germany	0.301	1,163.959	0.020	93,131	5.021	1,487
Greece	0.349	1.940	0.003	9	0.002	348
Hungary	0.368	2.978	0.009	0	0.000	58
Iceland	0.338	1.683	0.010	82	0.208	36
India	0.520	81.683	0.004	15,070	0.204	4,404
Indonesia	0.463	0.707	0.000	10	0.001	720
Ireland	0.330	159.188	0.034	30,541	14.683	184
Israel	0.337	61.894	0.083	3,320	0.390	702
Italy	0.326	121.637	0.007	1,785	0.255	620
Jamaica	0.436	0.002	0.000	0	0.000	46
Japan	0.367	2,780.538	0.011	712,120	7.586	5476
Jordan	0.384	0.081	0.000	0	0.000	238
Kazakhstan	0.365	0.053	0.000	0	0.000	41
Kenya	0.538	0.002	0.000	0	0.000	58
Korea, Rep.	0.376	413.217	0.016	158,964	4.266	2,440
Kuwait	0.418	0.004	0.000	0	0.000	219
Latvia	0.396	0.127	0.005	0	0.000	37
Lithuania	0.392	0.022	0.000	0	0.000	51
Luxembourg	0.296	8.778	0.003	421	0.399	108
Malawi	0.564	0.001	0.000	0	0.000	9
Malaysia	0.374	5.382	0.003	0	0.000	1,382
Malta	0.354	0.076	0.005	0	0.000	30
Mauritius	0.449	0.000	0.000	0	0.000	68
Mexico	0.415	1.584	0.000	18	0.006	212
Morocco	0.407	0.228	0.001	0	0.000	90
Netherlands	0.347	267.005	0.017	38,496	8.827	378
New Zealand	0.328	4.072	0.029	264	0.081	258
Nigeria	0.512	0.076	0.001	0	0.000	173

North Macedonia	0.386	0.000	0.000	0	0.000	1
Norway	0.265	22.616	0.018	868	0.168	505
Oman	0.428	0.002	0.000	0	0.000	110
Pakistan	0.539	0.365	0.000	0	0.000	474
Panama	0.401	0.021	0.004	0	0.000	3
Peru	0.458	0.145	0.000	1	0.000	132
Philippines	0.487	0.717	0.002	0	0.000	311
Poland	0.332	1.280	0.003	0	0.000	972
Portugal	0.348	0.421	0.000	0	0.000	109
Qatar	0.389	0.002	0.000	0	0.000	49
Romania	0.413	0.049	0.000	0	0.000	161
Russian Federation	0.353	17.523	0.001	7	0.002	350
Saudi Arabia	0.410	7.641	0.000	249	0.096	197
Serbia	0.419	0.056	0.000	0	0.000	26
Singapore	0.404	22.038	0.004	4,868	0.373	979
Slovak Republic	0.357	0.081	0.001	0	0.000	21
Slovenia	0.338	2.177	0.007	0	0.000	42
South Africa	0.417	6.168	0.001	199	0.027	605
Spain	0.310	32.062	0.040	208	0.049	352
Sri Lanka	0.478	0.030	0.000	0	0.000	295
Sudan	0.611	0.000	0.000	0	0.000	1
Sweden	0.302	248.511	0.057	26,051	2.195	1,093
Switzerland	0.273	520.428	0.027	36,248	5.400	468
Tanzania	0.546	0.000	0.000	0	0.000	14
Thailand	0.433	1.208	0.000	3	0.000	909
Trinidad and Tobago	0.398	0.002	0.000	0	0.000	21
Tunisia	0.397	0.026	0.000	0	0.000	78
Turkey	0.370	493.635	0.003	81	0.013	455
Uganda	0.586	0.000	0.000	0	0.000	9
Ukraine	0.392	0.394	0.001	0	0.000	46
United Arab Emirates	0.382	0.025	0.000	0	0.000	140
United Kingdom	0.300	635.767	0.024	36,927	0.789	4,416
United States	0.350	5,535.032	0.057	1,197,109	10.693	13,174
Venezuela, RB	0.381	0.111	0.001	0	0.000	36
Vietnam	0.491	0.032	0.000	0	0.000	589
Zambia	0.536	0.038	0.026	0	0.000	22
Zimbabwe	0.529	3.211	0.001	0	0.000	47

Panel B: Descriptive statistics for the full sample

Variable	Mean	Std. Dev.	Min	P25	Median	P75	Max	N
R&D$_{t+1}$	0.015	0.051	0.000	0.000	0.000	0.001	0.353	743,870
LnPatents$_{t+1}$	0.131	0.651	0.000	0.000	0.000	0.000	9.093	743,870
LnCitations$_{t+1}$	0.187	0.949	0.000	0.000	0.000	0.000	11.934	743,870
Vulnerability	0.380	0.066	0.249	0.341	0.366	0.407	0.619	743,870
Size	5.017	2.363	−0.650	3.470	4.950	6.507	11.111	739,562
M/B	2.585	4.926	−3.573	0.726	1.333	2.585	39.186	606,942
Tangibility	0.268	0.240	0.000	0.052	0.214	0.423	0.905	702,393
Cash	0.167	0.189	0.000	0.035	0.099	0.225	0.902	629,565
Free cash flow	0.009	0.185	−1.188	0.001	0.038	0.081	0.285	728,685
Leverage	0.232	0.218	0.000	0.040	0.190	0.362	1.043	690,589
ROA	0.049	0.190	−1.107	0.021	0.073	0.130	0.401	728,685
Capex	0.054	0.066	0.000	0.012	0.032	0.069	0.370	563,009
LnGDPpcap	9.556	1.408	5.012	8.658	10.264	10.608	11.685	743,870
GDP growth	0.037	0.032	−0.177	0.018	0.032	0.055	0.262	743,861
Political stability	0.187	0.873	−2.810	−0.499	0.410	0.937	1.760	648,333
Uncertainty	0.054	0.048	0.000	0.023	0.043	0.075	0.540	738,811
Property rights	0.683	0.232	0.050	0.500	0.793	0.900	0.984	698,373
Credit market	1.173	0.533	0.002	0.709	1.244	1.622	3.090	710,267
Equity market	0.860	0.471	0.006	0.528	0.782	1.153	3.522	706,339
HDI	0.805	0.123	0.362	0.727	0.862	0.897	0.954	743,668

Table 2
Climate vulnerability and R&D investment

This table shows the effect of climate vulnerability on R&D investment. The OLS regression is: $R\&D_{i,j,t+1} = \beta_0 + \beta_1 Vulnerability_{j,t} + \delta'X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t+1}$. The dependent variable $R\&D_{i,j,t+1}$ is the R&D investment of firm *i* in country *j* in year *t*+1, defined as R&D expenses scaled by total assets in year *t*+1. *Vulnerability* is a country's vulnerability to climate disruptions in year *t*. The vector *X* includes a set of firm-specific control variables as well as country-level factors measured in year *t*. The coefficients and standard errors for *Size* and *M/B* are multiplied by 100. All variables are defined in the Appendix. Firm and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $R\&D_{t+1}$			
	(1)	(2)	(3)	(4)
Vulnerability	−0.114***	−0.055***	−0.134***	−0.109***
	(0.002)	(0.011)	(0.015)	(0.024)
Size			−0.041**	−0.019
			(0.019)	(0.022)
M/B			0.002	0.006**
			(0.002)	(0.003)
Tangibility			0.002***	0.002**
			(0.001)	(0.001)
Cash			0.002**	0.002
			(0.001)	(0.001)
Free cash flow			−0.004**	−0.003
			(0.002)	(0.002)
Leverage			−0.007***	−0.007***
			(0.001)	(0.001)
ROA			−0.020***	−0.021***
			(0.002)	(0.002)
LnGDPpcap				0.001
				(0.001)
GDP growth				−0.015***
				(0.002)
Political stability				0.001***
				(0.000)
Uncertainty				−0.001
				(0.001)
Property rights				−0.000
				(0.001)
Credit market				0.002***
				(0.001)
Equity market				−0.002***
				(0.000)
HDI				0.030***
				(0.010)
Firm fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes
Observations	743,870	743,870	515,423	401,509
Adjusted R^2	0.022	0.787	0.815	0.821

Table 3
Climate vulnerability and innovation output

This table shows the effect of climate vulnerability on innovation output. In Columns 1-2, the dependent variables $LnPatents_{t+1}$ and $LnPatents_{t+1,\ t+3}$ are defined as the natural logarithm of one plus the number of successful patent applications filed by firm *i* in country *j* in year *t*+1 and the subsequent three years (*t*+1, *t*+2, and *t*+3), respectively. In Columns 3-4, the dependent variables $Ln\text{Citations}_{t+1}$ and $Ln\text{Citations}_{t+1,\ t+3}$ are defined as the natural logarithm of one plus the number of citations received by patents filed by firm *i* in country *j* in year *t*+1 and the subsequent three years (*t*+1, *t*+2, and *t*+3), respectively. *Vulnerability* is the climate vulnerability of country *j* in year *t*. The coefficient and standard error for *M/B* are multiplied by 100. All variables are defined in the Appendix. Firm and year fixed effects are included. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	LnPatents_{t+1}	$\text{LnPatents}_{t+1,t+3}$	LnCitations_{t+1}	$\text{LnCitations}_{t+1,\ t+3}$
	(1)	(3)	(4)	(6)
Vulnerability	−5.511***	−9.040***	−3.761***	−3.478***
	(0.463)	(0.667)	(0.815)	(1.049)
Size	0.029***	0.028***	0.019***	0.013**
	(0.002)	(0.003)	(0.005)	(0.006)
M/B	0.056**	0.081**	0.042	0.037
	(0.023)	(0.033)	(0.046)	(0.059)
Tangibility	0.043***	0.082***	0.150***	0.201***
	(0.007)	(0.011)	(0.016)	(0.022)
Cash	0.036***	0.079***	0.100***	0.143***
	(0.009)	(0.013)	(0.019)	(0.025)
Free cash flow	0.053***	0.094***	0.158***	0.220***
	(0.018)	(0.026)	(0.036)	(0.046)
Leverage	−0.055***	−0.110***	−0.142***	−0.197***
	(0.008)	(0.012)	(0.017)	(0.023)
ROA	−0.062***	−0.095***	−0.175***	−0.229***
	(0.019)	(0.028)	(0.039)	(0.050)
R&D	0.169***	0.219***	0.412***	0.465***
	(0.046)	(0.071)	(0.102)	(0.133)
Capex	−0.004	0.010	0.028	0.046*
	(0.010)	(0.014)	(0.021)	(0.027)
LnGDPpcap	−0.079***	−0.217***	−0.096***	−0.170***
	(0.010)	(0.014)	(0.015)	(0.020)
GDP growth	−0.030	−0.025	0.188***	0.225***
	(0.032)	(0.045)	(0.061)	(0.079)
Political stability	0.058***	0.057***	−0.071***	−0.131***
	(0.005)	(0.007)	(0.009)	(0.012)
Uncertainty	0.085***	0.085***	0.036	−0.032
	(0.022)	(0.030)	(0.033)	(0.042)
Property rights	0.218***	0.531***	0.454***	0.726***
	(0.019)	(0.029)	(0.037)	(0.048)
Credit market	0.031***	0.044***	−0.050***	−0.089***
	(0.009)	(0.013)	(0.018)	(0.023)
Equity market	−0.086***	−0.167***	−0.146***	−0.222***
	(0.006)	(0.008)	(0.010)	(0.013)
HDI	2.243***	6.360***	8.989***	14.201***
	(0.149)	(0.236)	(0.345)	(0.460)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	376,929	376,929	376,929	376,929
Adjusted R^2	0.835	0.846	0.703	0.736

Table 4
Climate vulnerability and the sensitivity of R&D to the investment opportunity set

This table shows the sensitivity of R&D investment to the investment opportunity set (*Tobin's Q*) conditional on the level of climate vulnerability. The OLS regression is: $R\&D_{i,j,t+1} = \beta_0 + \beta_1\ Tobin's\ Q_{i,j,t} \times Vulnerability_{j,t} + \beta_2\ Tobin's\ Q_{i,j,t} + \beta_3\ Vulnerability_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t+1}$. The dependent variable $R\&D_{i,j,t+1}$ is the R&D investment of firm *i* in country *j* in year *t*+1. *Tobin's Q* is calculated as (total assets + market value of equity – book value of equity – deferred taxes) divided by total assets in year *t*. *Vulnerability* is a country's vulnerability to climate disruptions in year *t*. Firm and year fixed effects are included. The coefficients and standard errors for *M/B* and *Political stability* are multiplied by 100. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $R\&D_{t+1}$	
	(1)	(2)
Tobin's Q × Vulnerability	−0.016***	−0.015***
	(0.001)	(0.001)
Tobin's Q	0.008***	0.007***
	(0.000)	(0.001)
Vulnerability	−0.087***	−0.047*
	(0.013)	(0.025)
Size		−0.003***
		(0.000)
M/B		0.015***
		(0.003)
Tangibility		0.006***
		(0.001)
Cash		−0.002
		(0.001)
Free cash flow		−0.004**
		(0.002)
Leverage		−0.009***
		(0.001)
ROA		−0.020***
		(0.002)
LnGDPpcap		0.004***
		(0.001)
GDP growth		−0.017***
		(0.003)
Political stability		0.030
		(0.031)
Uncertainty		0.001
		(0.001)
Property rights		0.001
		(0.001)
Credit market		0.002**
		(0.001)
Equity market		−0.002***
		(0.000)
HDI		0.028***
		(0.011)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	607,131	401,509
Adjusted R^2	0.821	0.831

Table 5
The relation between climate vulnerability and incentive to innovate

This table shows the effect of climate vulnerability on the number of patent inventors. Following Bhattacharya et al. (2017), the estimated regression is: $LnInventors_{k,j,t+1} = \beta_0 + \beta_1 Vulnerability_{j,t} + \delta' X + Country\text{-}industry\ FE + Year\ FE + \varepsilon_{k,j,t+1}$. The dependent variable $LnInventors_{k,j,t+1}$ is the natural logarithm of one plus the number of inventors who have ever filed at least one patent of industry *k* of country *j* in year *t*+1. *Vulnerability* is country *j*'s vulnerability to climate disruptions in year *t*. The vector *X* includes a set of country-level factors measured in year *t* as well as the lagged number of inventors ($LnInventors_{k,j,t}$). Country-industry and year fixed effects are included. Numbers in parentheses are two-way clustered standard errors by country-industry and by year. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $LnInventors_{t+1}$		
	(1)	(2)	(3)
Vulnerability	−2.041*	−1.872***	−2.268***
	(1.116)	(0.643)	(0.719)
$LnInventors_t$		0.588***	0.572***
		(0.045)	(0.054)
LnGDPpcap			−0.013
			(0.018)
GDP growth			−0.067
			(0.049)
Political stability			0.008
			(0.007)
Uncertainty			−0.051
			(0.065)
Property rights			0.080*
			(0.041)
Credit market			0.020
			(0.013)
Equity market			−0.033**
			(0.012)
HDI			0.792**
			(0.307)
Country-industry fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	61,836	58,552	40,755
Adjusted R^2	0.907	0.934	0.931

Table 6
The effects of climate vulnerability on patent grant announcement abnormal returns and patent value

Panel A shows mean and median CARs in percentage during the window of (0,+2) around the patent grant announcement date for the subsamples of high and low vulnerability (sorted by the yearly median of climate vulnerability index). For market-adjusted returns, the raw returns are adjusted by the CRSP value-weighted market returns or the country total return indices from World Indices by WRDS database. The *t*-statistics or *p*-values of the tests of difference in means (*t*-test) and in medians (Wilcoxon rank sum test) are reported at the bottom; *t*-statistics and *p*-values of Wilcoxon signed-rank test are reported in parentheses. Panel B shows the effect of climate vulnerability on patent value. The dependent variable $Patent\ value_{t+1}$ is the market value of each patent grant (in ten million U.S. dollars) in year *t*+1, measured as the firm's stock return in excess of the market return over the three-day window around the date of patent approval and multiplied by the firm's market capitalization on the day prior to the announcement. *Vulnerability* is country *j*'s climate vulnerability in year *t*. Firm and year fixed effects are included. Numbers in parentheses are robust clustered standard errors by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Patent grant announcement abnormal returns and climate vulnerability

	Market-adjusted returns		Raw returns		
	Mean	Median	Mean	Median	Number of patent grants
High vulnerability	0.027***	−0.140***	0.188***	0.000***	1,211,738
	(8.25)	(<.0001)	(48.16)	(<.0001)	
Low vulnerability	0.062***	−0.018***	0.227***	0.162***	1,647,912
	(19.69)	(<.0001)	(44.33)	(<.0001)	
Difference (High − Low)	−0.035***	−0.123***	−0.039***	−0.162***	
	(−7.65)	(<.0001)	(−6.07)	(<.0001)	

Panel B: Patent value and climate vulnerability

	Dependent variable: Patent value$_{t+1}$	
	(1)	(2)
Vulnerability	−3.068**	−6.030**
	(1.499)	(2.835)
Size		−0.195***
		(0.036)
M/B		−0.074***
		(0.006)
Tangibility		2.338***
		(0.264)
Cash		0.949***
		(0.166)
Free cash flow		1.039***
		(0.316)
Leverage		1.905***
		(0.126)
ROA		−1.461***
		(0.323)
R&D		0.451*
		(0.239)
Capex		−1.349***
		(0.496)
LnGDPpcap		0.023
		(0.127)
GDP growth		−0.052***
		(0.010)
Political stability		−0.021
		(0.070)
Uncertainty		2.089***
		(0.369)
Property rights		0.240
		(0.261)
Credit market		0.074
		(0.104)
Equity market		−0.181*
		(0.105)
HDI		−5.445**
		(2.518)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	2,654,125	2,396,302
Adjusted R^2	0.010	0.011

Table 7
Subsample analysis for the relation between climate vulnerability and R&D investment

This table shows subsample results of the effect of climate vulnerability on R&D investment based on Equation (1). In Columns 1-2, the sample of Table 2 is divided into high and low groups by the median of product development cycle, measured as the industry-level R&D amortizable life. In Columns 3-4, our sample is divided into high and low groups by the median of Google search volume within each country for terms associated with the topic of "Climate variability and change". Columns 5-6 report the subsample results for developed and developing countries. The dependent variable $R\&D_{i,j,t+1}$ is the R&D investment of firm *i* in country *j* in year *t*+1. *Vulnerability* is country *j*'s climate vulnerability in year *t*. The coefficients and standard errors for *Size* and *M/B* are multiplied by 100. All variables are defined in the Appendix. Firm and year fixed effects are included where indicated. Numbers in brackets are *z*-statistics for the tests of the difference in coefficients of *Vulnerability* between two subsamples. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $R\&D_{t+1}$					
	Product development cycle		Google search volume		Developed countries	Developing countries
	high	low	high	low		
	(1)	(2)	(3)	(4)	(5)	(6)
Vulnerability	−0.153***	−0.068*	−0.181***	−0.074**	−0.087**	−0.024***
	(0.033)	(0.036)	(0.042)	(0.038)	(0.040)	(0.005)
Size	0.038	−0.106***	0.110***	0.057	−0.057**	0.048***
	(0.031)	(0.031)	(0.033)	(0.035)	(0.024)	(0.007)
M/B	0.003	0.008**	−0.001	0.005	0.006**	0.002***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.001)
Tangibility	0.005***	−0.001	0.002	−0.000	0.003***	−0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Cash	0.008***	−0.007***	0.002	0.002	0.003**	−0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.000)
Free cash flow	0.000	−0.006**	0.002	0.004	0.002	−0.004***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)
Leverage	−0.008***	−0.005***	−0.008***	−0.005***	−0.006***	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
ROA	−0.027***	−0.011***	−0.020***	−0.020***	−0.019***	0.004***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)
LnGDPpcap	−0.001*	0.003***	0.001	−0.001	−0.002***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
GDP growth	−0.025***	−0.002	−0.004	−0.017***	0.009***	−0.018***
	(0.003)	(0.003)	(0.004)	(0.006)	(0.004)	(0.001)
Political stability	0.002***	0.000	0.001	−0.001**	−0.000	−0.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Uncertainty	−0.003	0.002	−0.005**	0.001	−0.000	−0.003***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
Property rights	0.001	−0.003*	0.004***	−0.008***	−0.008***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.000)
Credit market	0.002*	0.003***	0.005***	0.001	0.001*	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Equity market	−0.002***	−0.001**	−0.001	−0.004***	−0.003***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
HDI	0.071***	−0.027*	−0.008	0.016	0.061***	0.018***
	(0.014)	(0.015)	(0.015)	(0.019)	(0.012)	(0.002)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,595	175,914	156,880	164,992	271,428	130,081
Adjusted R^2	0.840	0.757	0.857	0.843	0.845	0.706
Difference	−0.085*		−0.107*		−0.063	
z-statistic	[−1.75]		[−1.90]		[−1.57]	

Table 8
Climate vulnerability and innovation strategies

This table shows the effect of climate vulnerability on innovation strategies. A patent is classified as climate change mitigation technologies (CCMTs) if its Cooperative Patent Classification (CPC) is Y02 or Y04S. A patent is categorized as exploitative if at least 60% of its citations are based on the firm's existing knowledge and as exploratory, if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge). The dependent variables *CCMT ratio*, *Exploratory ratio*, and *Exploitative ratio* are defined as the number of CCMT patents, exploratory, or exploitative patents filed by firm *i* in country *j* over years *t*+1 to *t*+3 divided by the total number of patents filed by firm *i* over years *t*+1 to *t*+3. *Vulnerability* is country *j*'s climate vulnerability in year *t*. The sample is restricted to firms that have filed at least one patent during our sample period. The coefficients and standard errors for *M/B* are multiplied by 100. All variables are defined in the Appendix. Firm and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	CCMT ratio	Exploratory ratio	Exploitative ratio
	(1)	(2)	(3)
Vulnerability	0.323**	−1.658**	1.026*
	(0.154)	(0.653)	(0.619)
Size	0.001	0.007***	0.016***
	(0.001)	(0.002)	(0.002)
M/B	0.006	0.018	0.073***
	(0.006)	(0.024)	(0.022)
Tangibility	−0.028***	−0.045**	−0.026**
	(0.006)	(0.021)	(0.013)
Cash	−0.004*	0.002	0.006
	(0.002)	(0.011)	(0.008)
Free cash flow	0.011**	−0.019	0.029*
	(0.004)	(0.024)	(0.017)
Leverage	0.005**	−0.025***	0.009
	(0.002)	(0.009)	(0.008)
ROA	−0.011**	0.021	−0.020
	(0.005)	(0.025)	(0.017)
R&D	0.012	−0.090***	0.067**
	(0.008)	(0.031)	(0.027)
Capex	−0.002	0.048	0.025
	(0.012)	(0.043)	(0.026)
LnGDPpcap	0.041***	0.176***	0.079***
	(0.005)	(0.017)	(0.011)
GDP growth	−0.008	0.145	−0.196*
	(0.037)	(0.143)	(0.111)
Political stability	0.013***	0.069***	−0.007
	(0.003)	(0.009)	(0.006)
Uncertainty	−0.013	−0.046	0.002
	(0.015)	(0.050)	(0.037)
Property rights	−0.053***	−0.532***	−0.356***
	(0.010)	(0.037)	(0.026)
Credit market	−0.024***	−0.017	0.028***
	(0.003)	(0.014)	(0.010)
Equity market	−0.002	−0.033***	0.005
	(0.003)	(0.012)	(0.008)
HDI	−0.419***	−3.959***	−1.314***
	(0.072)	(0.314)	(0.187)
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	56,543	56,543	56,543
Adjusted R^2	0.430	0.377	0.427

Table 9
Climate-related natural disasters and R&D investment: Difference-in-differences regression analysis

This table shows the effect of climate-related natural disasters on R&D investment using a difference-in-differences (DID) regression analysis. These events include the 2003 European heatwave (especially France), the 2004 Asian tsunami, Japan's 2011 earthquake and tsunami, and Thailand's 2011 flooding. The DID regression is as follows: $R\&D_{i,j,t} = \beta_0 + \beta_1 Treat_j \times Post_{j,t} + \delta' X + Firm\ FE + Year\ FE + \varepsilon_{i,j,t}$. The dependent variable $R\&D_{i,j,t}$ is the R&D investment of firm i in country j in year t. $Treat_j$ is a dummy equal to one for the treated country j and zero otherwise. $Post_{j,t}$ is a dummy that equals one for post-disaster years and zero otherwise. The vector X includes the same control variables as in Equation (1). Firm and year fixed effects are included where indicated. *Treat* and *Post* dummies are omitted due to collinearity with fixed effects. Columns 1, 3, 5, 7, and 9 use all other countries as the control groups, while Columns 2, 4, 6, 8, and 10 only use the treated country or countries. The DID regression uses an event window of (y−3, y+3) around a natural disaster event. The most affected countries by the 2003 European heatwave include France, Germany, Spain, Italy, UK, Netherlands, Portugal, Belgium, Switzerland, Austria, Finland, Denmark, and Ireland. For the 2004 Asian tsunami, our sample includes the 6 most-affected countries: Indonesia, Sri Lanka, India, Thailand, Malaysia, and Tanzania. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent variable: $R\&D_{t+1}$									
	2003 France heatwave		2003 European heatwave		2004 Asian tsunami		Japan 2011 earthquake & tsunami		Thailand 2011 flooding	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Treat × Post	−0.007***	−0.009***	−0.003***	−0.012***	−0.001***	−0.001***	−0.001**	−0.003***	−0.001**	−0.001*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Observations	79,063	2,057	79,063	14,645	97,758	28,500	153,576	22,955	153,576	2,410
Adjusted R^2	0.863	0.748	0.863	0.744	0.859	0.474	0.863	0.865	0.887	0.898

Table 10
Robustness checks: Firm-level climate change exposure

This table shows the effect of firm-level climate risk exposure on R&D investment and innovation performance. The firm-level measures of climate change exposure are constructed by Sautner, van Lent, Vilkov, and Zhang (2020), using transcripts of quarterly earnings conference calls. By their definition, climate change exposure (*CCExposure*) is based on the frequency of climate change bigrams that occur in a given transcript, scaled by the total number of bigrams in the transcript. The measure of climate change risk (*CCRisk*) is constructed by counting the relative frequency of climate change bigrams mentioned in the same sentence with the words "risk" or "uncertainty" (or their synonyms). The value of *CCExposure* and *CCRisk* are multiplied by 1000. The sample period is 2002-2019. Country, industry, and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. The coefficients and standard errors for *M/B* are multiplied by 100. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	$R\&D_{t+1}$		$LnPatents_{t+1}$		$LnCitations_{t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
CCExposure	−0.002***		−0.010**		−0.012**	
	(0.000)		(0.004)		(0.005)	
CCRisk		−0.011***		−0.081**		−0.099**
		(0.003)		(0.039)		(0.048)
Size	−0.003***	−0.003***	0.365***	0.366***	0.360***	0.361***
	(0.000)	(0.000)	(0.014)	(0.014)	(0.014)	(0.014)
M/B	0.095***	0.096***	0.991***	0.992***	0.838***	0.840***
	(0.012)	(0.012)	(0.170)	(0.170)	(0.183)	(0.182)
Tangibility	0.001	−0.001	−0.167**	−0.176**	−0.130	−0.139
	(0.003)	(0.003)	(0.078)	(0.078)	(0.085)	(0.085)
Cash	0.136***	0.137***	1.108***	1.111***	1.277***	1.280***
	(0.005)	(0.005)	(0.084)	(0.084)	(0.096)	(0.096)
Free cash flow	−0.053***	−0.053***	−0.193	−0.190	−0.028	−0.024
	(0.009)	(0.009)	(0.142)	(0.142)	(0.161)	(0.161)
Leverage	−0.010***	−0.009***	−0.470***	−0.468***	−0.481***	−0.479***
	(0.003)	(0.003)	(0.065)	(0.065)	(0.074)	(0.074)
ROA	−0.144***	−0.143***	0.289**	0.293**	0.058	0.062
	(0.009)	(0.009)	(0.146)	(0.145)	(0.163)	(0.163)
LnGDPpcap	0.010***	0.010***	0.086	0.088	−0.230**	−0.227**
	(0.003)	(0.003)	(0.093)	(0.092)	(0.116)	(0.116)
GDP growth	0.012	0.012	−1.842***	−1.844***	−1.366**	−1.368**
	(0.018)	(0.018)	(0.432)	(0.432)	(0.547)	(0.547)
Political stability	0.004**	0.004**	0.143***	0.142***	−0.061	−0.061
	(0.002)	(0.002)	(0.053)	(0.053)	(0.073)	(0.073)
Uncertainty	0.006	0.006	0.833***	0.838***	0.966***	0.972***
	(0.005)	(0.005)	(0.169)	(0.169)	(0.200)	(0.200)
Property rights	−0.020***	−0.021***	−1.701***	−1.708***	−1.564***	−1.572***
	(0.008)	(0.008)	(0.276)	(0.276)	(0.352)	(0.352)
Credit market	0.005	0.004	0.018	0.016	0.189*	0.187*
	(0.003)	(0.003)	(0.083)	(0.083)	(0.110)	(0.111)
Equity market	0.005**	0.005**	−0.421***	−0.421***	−0.713***	−0.713***
	(0.002)	(0.002)	(0.066)	(0.066)	(0.089)	(0.089)
HDI	−0.032	−0.037	0.887	0.871	9.009***	8.997***
	(0.056)	(0.057)	(1.677)	(1.675)	(2.140)	(2.140)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,408	59,408	59,408	59,408	59,408	59,408
Adjusted R^2	0.617	0.615	0.422	0.421	0.382	0.382

Internet Appendix

Table IA1
Average cross-country time-series correlations

This table reports the average cross-country time-series correlations of our main variables. The time-series correlations of the variables are calculated for each country. The statistics reported are the averages of these correlations across all the countries.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) Vulnerability																			
(2) R&D$_{t+1}$	−0.022																		
(3) LnPatents$_{t+1}$	0.023	0.083																	
(4) LnCitations$_{t+1}$	0.053	0.073	0.850																
(5) Size	−0.011	−0.094	0.200	0.167															
(6) M/B	−0.008	0.051	0.015	0.016	−0.023														
(7) Tangibility	0.031	−0.118	−0.010	−0.005	0.157	−0.062													
(8) Cash	−0.020	0.156	0.015	0.015	−0.116	0.116	−0.327												
(9) Free cash flow	0.029	−0.121	0.052	0.046	0.239	0.027	0.118	−0.041											
(10) Leverage	−0.019	−0.066	−0.012	−0.011	0.169	−0.023	0.217	−0.339	−0.181										
(11) ROA	0.038	−0.114	0.060	0.055	0.230	0.095	0.095	0.006	0.889	−0.156									
(12) Capex	0.052	−0.032	0.011	0.015	0.064	0.052	0.382	−0.086	0.165	0.078	0.169								
(13) LnGDPpcap	−0.303	0.028	−0.023	−0.076	0.060	0.023	−0.047	0.023	−0.029	−0.002	−0.046	−0.034							
(14) GDP growth	0.027	0.007	0.000	0.015	−0.008	0.055	−0.011	0.013	0.050	−0.029	0.054	0.051	−0.034						
(15) Political stability	0.024	−0.004	0.013	0.025	0.005	0.015	0.016	−0.005	0.010	0.008	0.011	0.030	−0.013	0.053					
(16) Uncertainty	−0.130	0.012	−0.024	−0.036	0.001	−0.010	−0.011	0.005	−0.027	0.013	−0.035	−0.040	0.078	−0.125	−0.069				
(17) Property rights	−0.034	0.011	0.000	0.007	−0.003	−0.004	−0.008	0.012	−0.009	0.011	−0.015	−0.028	0.055	−0.061	0.146	0.004			
(18) Credit market	−0.248	0.015	−0.014	−0.033	0.039	−0.001	−0.015	0.000	−0.029	0.022	−0.041	−0.014	0.306	−0.251	−0.060	0.096	0.039		
(19) Equity market	0.020	0.004	−0.008	−0.004	0.031	0.072	−0.017	0.025	0.027	−0.041	0.028	0.030	−0.031	0.239	0.000	−0.112	−0.053	0.056	
(20) HDI	−0.524	0.044	−0.052	−0.106	0.027	0.021	−0.056	0.032	−0.050	0.021	−0.065	−0.095	0.645	−0.119	−0.083	0.247	0.115	0.359	−0.026

Table IA2
Subsamples by innovation strategies

This table shows the subsample results of innovation strategies. A patent is classified as climate change mitigation technologies (CCMTs) if its Cooperative Patent Classification (CPC) is Y02 or Y04S. A patent is categorized as exploitative if at least 60% of its citations are based on the firm's existing knowledge and as exploratory if at least 60% of its citations are based on new knowledge (i.e., patents not in the firm's existing knowledge). The dependent variables *LnNonCCMT*, *LnCCMT*, *LnExploratory*, and *LnExploitative* are defined as the natural logarithm of one plus the number of non-CCMT patents, CCMT patents, exploratory patents, or exploitative patents filed by firm *i* in country *j* in year *t*+1 or over years *t*+1 to *t*+3, respectively. *Vulnerability* is country *j*'s climate vulnerability in year *t*. All variables are defined in the Appendix. Firm and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. Numbers in brackets are *z*-statistics for the tests of the difference in coefficients of *Vulnerability* between two subsamples. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$LnNonCCMT_{t+1}$	$LnCCMT_{t+1}$	$LnNonCCMT_{t+1, t+3}$	$LnCCMT_{t+1, t+3}$	$LnExploratory_{t+1}$	$LnExploitative_{t+1}$	$LnExploratory_{t+1, t+3}$	$LnExploitative_{t+1, t+3}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerability	−5.266***	−1.897***	−8.823***	−3.617***	−7.106***	−5.245***	−4.553***	−3.088***
	(0.456)	(0.226)	(0.660)	(0.335)	(0.601)	(0.372)	(0.446)	(0.268)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	376,929	376,929	376,929	376,929	376,929	376,929	376,929	376,929
Adjusted R^2	0.835	0.714	0.845	0.750	0.806	0.811	0.793	0.788
Difference	−3.370***		−5.206***		−1.861***		−1.465***	
z-statistic	[−6.62]		[−7.03]		[−2.63]		[−2.82]	

Table IA3
Robustness checks: Alternative measure of climate vulnerability

This table reports the results using alternative measures of climate vulnerability. The sample period is 1995-2019. Panel A uses the Global Climate Risk Index (CRI) compiled and published by Germanwatch to measure climate risk by country. *Climate Risk Index* is the Climate Risk Index score of country *j* in year *t* multiplied by −1 so that a higher score indicates greater climate risk. *Climate Risk Index* is divided by 100 in regressions. Panel B uses the Notre Dame-Global Adaptation Index (ND-GAIN) Country Index. This index measures both dimensions: climate vulnerability and readiness. It shows a country's current vulnerability to climate disruptions and also assesses a country's readiness to leverage private and public sector investment for adaptive actions. The ND-GAIN score is computed by subtracting the vulnerability score from the readiness score for each country, and scale the scores to give a value 0 to 100: ND-GAIN score = (readiness score − vulnerability score +1) * 50. The ND-GAIN score is divided by 100 in regressions. Firm and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Germanwatch Global Climate Risk Index

Dependent variable:	R&D$_{t+1}$	LnPatents$_{t+1}$	LnCitations$_{t+1}$	LnPatents$_{t+1,t+3}$	LnCitations$_{t+1,t+3}$
	(1)	(2)	(3)	(4)	(5)
Climate Risk Index	−0.001**	−0.016***	−0.109***	−0.067***	−0.182***
	(0.000)	(0.006)	(0.011)	(0.009)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	401,472	376,893	376,893	376,893	376,893
Adjusted R^2	0.821	0.835	0.703	0.845	0.736

Panel B: Notre Dame-Global Adaptation Index (ND-GAIN)

Dependent variable:	R&D$_{t+1}$	LnPatents$_{t+1}$	LnCitations$_{t+1}$	LnPatents$_{t+1,t+3}$	LnCitations$_{t+1,t+3}$
	(1)	(2)	(3)	(4)	(5)
ND-GAIN score	0.089***	1.372***	0.499***	2.474***	1.175***
	(0.011)	(0.160)	(0.183)	(0.239)	(0.436)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	401,509	376,929	376,929	376,929	376,929
Adjusted R^2	0.821	0.835	0.703	0.846	0.736

Table IA4
Robustness checks: Alternative measures of innovation input & output and alternative fixed effects

Panel A reports results using alternative measures of innovation input and output. For Columns 1-2, the dependent variables $R\&D_{i,j,t+2}$ and $R\&D_{i,j,t+3}$ are the R&D expenses scaled by total assets of firm *i* in country *j* in year *t*+2 or *t*+3. In Column 3, the dependent variable $R\&D\ growth_{t+1}$ is the R&D growth of firm *i* in country *j* in year *t*+1 and is defined as $ln(1 + R\&D_{i,j,t+1}) – ln(1 + R\&D_{i,j,t})$. For Columns 4-7, the dependent variables are the natural logarithm of one plus the number of patent applications (or citations received by patents) filed by firm *i* in country *j* in year *t*+2 or *t*+3. In Column 8, the dependent variable $Patent\ growth_{t+1}$ is the measure of innovation growth of firm *i* in country *j* in year *t*+1 and is defined as $ln(1 + Patent_{i,j,t+1}) – ln(1 + Patent_{i,j,t})$. *Vulnerability* is a country's vulnerability to climate disruptions in year *t*. The vector *X* includes a set of firm-specific control variables as well as country-level factors measured in year *t*. Panel B shows the results using alternative fixed effects. Firm, year, country, industry, country-industry, or industry-year fixed effects are included where indicated. All variables are defined in the Appendix. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative measures of innovation input and output

Dependent variable:	$R\&D_{t+2}$	$R\&D_{t+3}$	R&D $growth_{t+1}$	$LnPatents_{t+2}$	$LnPatents_{t+3}$	$LnCitations_{t+2}$	$LnCitations_{t+3}$	Patent $growth_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Vulnerability	−0.143***	−0.131***	−1.604***	−6.540***	−7.023***	−4.317***	−3.617***	−1.905***
	(0.025)	(0.026)	(0.255)	(0.425)	(0.437)	(1.027)	(1.054)	(0.185)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	359,318	320,858	401,455	338,894	303,232	338,894	303,232	376,929
Adjusted R^2	0.824	0.830	0.119	0.833	0.831	0.746	0.786	0.102

Panel B: Alternative fixed effects

Dependent variable:	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
vulnerability	−0.073**	−6.573***	−3.574***	−0.071***	−7.112***	−4.196***	−0.044**	−7.046***	−3.788***
	(0.034)	(0.435)	(0.689)	(0.026)	(0.445)	(0.708)	(0.018)	(0.420)	(0.664)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-industry fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Country fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Year fixed effects	No	No	No	No	No	No	Yes	Yes	Yes
Observations	400,907	376,504	376,504	400,907	376,504	376,504	400,907	376,504	376,504
Adjusted R^2	0.481	0.328	0.334	0.427	0.272	0.294	0.424	0.261	0.256

Table IA5
Robustness checks: Alternative samples

Panel A uses a subsample of non-U.S. firms. Panel B is restricted to firms with at least one patent application during our sample period. Panel C uses a sample period of 1995-2017 to mitigate the truncation issue due to the patent application-grant lag. Firm and year fixed effects are included where indicated. Numbers in parentheses are robust standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Non-US firms only

Dependent variable:	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$	$LnPatents_{t+1,t+3}$	$LnCitations_{t+1,t+3}$
	(1)	(2)	(3)	(4)	(5)
Vulnerability	−0.144***	−3.797***	−6.413***	−5.391***	−7.838***
	(0.023)	(0.412)	(0.720)	(0.573)	(0.892)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	318,261	297,563	297,563	297,563	297,563
Adjusted R^2	0.745	0.793	0.655	0.792	0.664

Panel B: Firms with at least one patent application during the sample period

Dependent variable:	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$	$LnPatents_{t+1,t+3}$	$LnCitations_{t+1,t+3}$
	(1)	(2)	(3)	(4)	(5)
Vulnerability	−0.045**	−15.299***	−47.714***	−23.596***	−51.705***
	(0.021)	(4.829)	(8.093)	(5.922)	(8.679)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	58,612	56,543	56,543	56,543	56,543
Adjusted R^2	0.910	0.824	0.712	0.837	0.760

Panel C: Sample period of 1995-2017

Dependent variable:	$R\&D_{t+1}$	$LnPatents_{t+1}$	$LnCitations_{t+1}$	$LnPatents_{t+1,t+3}$	$LnCitations_{t+1,t+3}$
	(1)	(2)	(3)	(4)	(5)
Vulnerability	−0.078***	−4.599***	−2.268***	−7.621***	−1.227**
	(0.024)	(0.384)	(0.753)	(0.557)	(0.607)
Controls	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	374,554	351,439	351,439	351,439	351,439
Adjusted R^2	0.823	0.865	0.724	0.874	0.756