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Inventors' Personal Experience of Natural Disasters and Green Innovation*

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Abstract

We show that personal experiences affect high-stakes economic decisions among inventors. Using matched patent and survey data from French and German inventors linked to natural disaster records, we exploit exogenous variation in disaster exposure. Inventors personally affected by natural disasters subsequently produce 8.2% more green patents, primarily driven by emission-reducing mitigation technologies, while non-green innovation remains unaffected. The absence of sizable spatial spillovers highlights the importance of personal experience. Disaster exposure shapes innovation choices by altering profitability expectations through shifting higher-order beliefs about consumer demand and anticipated regulation. Embedding this channel in a formal model, we disentangle the role of expectations and intrinsic motivation. The model predicts, and the data confirm, that effects are strongest in competitive markets, where profit incentives matter most.

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1 Introduction

What drives inventors to pursue new ideas? Popular accounts often point to moments of personal frustration that make unmet needs visible: Netflix is linked to an anecdote about a $40 late DVD return fee, while BioLite emerged when its founders sought a cleaner, lighter wood-burning camp stove instead of carrying heavy fossil-fuel canisters.[1] Such stories suggest that invention may often arise from personal experience rather than from systematic responses to markets. A rich literature links innovation to market conditions such as competition (Aghion and Howitt 1992; Aghion et al. 2005) and market size (Acemoglu 2002; Acemoglu and Linn 2004), but much less is known about inventor-level determinants. This is particularly relevant given persistent underinvestment in R&D despite its large social returns (Bloom et al. 2013; Azoulay et al. 2019; Jones and Summers 2020; Jones 2021), and the role of innovation in combating climate change (Acemoglu et al. 2012; Acemoglu et al. 2016). Social background and childhood socioeconomic status influence who becomes an inventor (Feng et al. 2021; Bell et al. 2019), but we know little about what ultimately drives their choices about what to innovate.

In this paper, we bring insights from the experience effects literature to the production side and explore how personal experiences shape inventors' choices. The experience effects literature has shown that households' personal experiences shape beliefs, preferences, and expectations (e.g., Malmendier and Nagel 2011; Malmendier and Nagel 2016; Giuliano and Spilimbergo 2024). Expectations, in particular about commercial success and profitability, matter for inventors, as pursuing innovation is inherently uncertain and risky (Rosenberg 1998; Bloom 2007; Manso 2011). Personal experiences plausibly play a role in forming these expectations. To explore the role of personal experiences, we first exploit natural disaster exposure as exogenous shocks to inventors' personal experience, allowing us to identify causal effects on subsequent green innovation. Green technologies either mitigate or adapt to climate change. To explore the underlying mechanisms, the second part of the paper examines how disaster exposure influences inventors' expectations about consumer demand for green goods and environmental regulation using survey data. In the third part of the paper, we propose a formal model that incorporates our behavioral mechanism into a quality-ladder model, and disentangles the roles of intrinsic motivation and profitability expectations.

We begin our analysis by linking French and German inventors' home addresses to natural disasters and use event-study designs to estimate the effects of natural disaster exposure on subsequent innovation. Our design exploits random variation in the timing of inven-

[1]Based on interviews with Netflix's Reed Hastings (CBS News 2006) and BioLite's Alec Drummond and Jonathan Cedar (Bastone 2018).

tors' exposure to natural disasters. We use patent data from 1994 to 2014 with geocoded addresses from De Rassenfosse et al. (2019). Disasters are matched spatially using the Emergency Events Database (Guha-Sapir et al. 2022), supplemented with geolocations from the Geocoded Disasters dataset (Rosvold and Buhaug 2021). We identify green patents using an established classification that tags technologies aimed at climate change mitigation or adaptation. Most inventors in our sample are affiliated with firms (72%), while a substantial share (16.8%) operates independently.

Our results show that natural disaster exposure leads to a significant increase in green innovation. On average, one additional natural disaster increases green patenting by 8.2% relative to the sample average. This impact evolves dynamically over time. Notably, five years after a disaster, the number of green patents rises by 24%, with the effect gradually tapering off thereafter. This 24% increase corresponds to 0.64 additional green patents in the affected region. In terms of magnitude, our estimate is comparable to the effect of the European Emissions Trading System (EU-ETS), which increased green patenting among covered firms by about 10% (see Calel and Dechezleprêtre 2016).

We find that disaster exposure only affects climate-related innovation, consistent with a salient link between personal experiences of natural disasters and climate change. Disaster exposure does not lead to significant changes in non-green innovation. This additionally suggests limited crowding out of other inventive activity. Green innovation increases significantly more following more deadly disasters, consistent with the idea that the salience of climate-related risks increases with disaster fatalities (Demski et al. 2017; Kalatzi Pantera et al. 2023). The green innovation response appears tied to the broader issue of climate change rather than to the specific disasters inventors experience. Disaster exposure increases patenting in mitigation technologies by 8.4 percent. These technologies aim to reduce greenhouse gas emissions and address the root causes of climate change, and are not tied to the type of event. In contrast, directly related adaptation technologies that address local climate impacts respond less strongly (4.4% increase).

Inventors respond only when personally affected; we find no evidence of large spillovers from natural disasters to nearby regions. Yet, the innovations that result from these local personal experiences have global reach and value, being both highly cited and frequently triadic. Triadic patents are those filed in the United States, Europe, and Japan, and are often used as a proxy for the most valuable technologies (Dernis and Khan 2004; Rassenfosse and Pottelsberghe de la Potterie 2009).

To explore the potential mechanisms behind this increase in green innovation, the second part of the paper links natural disasters to a survey of inventive firms, where most inventors work. We use data from the Community Innovation Survey (CIS), which asks research personnel in German firms about recent innovations and the reasons behind them.

Natural disaster exposure alters higher-order beliefs (beliefs about others' beliefs) regarding consumers' climate change attitudes, their consumption preferences and voting behavior. Experiencing one additional disaster raises the likelihood of citing expected increases in green demand as a motive for green innovation by 0.87 percentage points. It also increases the likelihood of citing anticipated environmental regulation by 0.93 percentage points. Exposed respondents do not report reputational concerns or increased government funding and subsidies as drivers of their green innovation. To further examine the role of government research funding, we match French administrative data on government research funding to our disaster exposure measure. We do not detect systematic increases in funding for affected regions. These results are consistent with a mechanism that primarily goes through expectations about the future profitability of green innovation. Natural disasters locally increase the salience of climate change, shifting consumption toward environmentally friendly products, and thus raise expectations of green demand and regulation.[2] As a result, inventors expect higher returns to green innovation and increase their R&D efforts accordingly.

Additionally, the CIS data allow us to capture innovations beyond those recorded in the patent system, which we use to confirm that affected firms are more likely to introduce green products and engage in green process innovation. Exposure increases the likelihood of introducing green process innovation and green product innovation by roughly 4.7% and 4.3%, respectively. Moreover, self-reported climate change affectedness is robustly correlated with our natural disaster measure.

In the third part of the paper, we embed our behavioral mechanism in a formal theoretical framework to examine how it interacts with market forces, allowing us to disentangle profitability expectations and intrinsic motivation. Building on Aghion et al. (2023), consumers value both the consumption utility and the carbon footprint of goods—for example, transportation and its associated emissions. Consumer preferences depend on beliefs about climate change. We extend this framework by modeling how inventors respond to the heightened salience of climate change. Inventors form expectations about the future profitability of green technologies and derive intrinsic utility from engaging in green research. Both expectations about profitability and intrinsic motives are shaped by local personal experiences with natural disasters. Inventors operate in markets with varying degrees of competition, which shapes how strongly they respond to changes in expected demand for green technologies. In monopolistic markets, inventors have little incentive to develop green alternatives, as incumbents already earn high profits. In contrast, in competitive markets, inventors face price

[2] Disaster exposure increases green good demand & environmental policy preferences (Djourelova et al. 2024, Chae et al. 2025).

pressure and can use green innovation to differentiate their products and escape competition.

Our model predicts that only inventors motivated by profitability expectations respond more strongly to natural disaster exposure when they operate in competitive markets. This comparative static provides a test of our proposed mechanism. Since market structure affects only the profit motive and not inventors' intrinsic motivation, a stronger innovation response in competitive markets would indicate that profit incentives play a central role. In contrast, if intrinsic motivation were the sole driver, inventors would respond equally regardless of the level of competition.

We test this comparative static empirically by matching our patent data with information on industry competition, and find evidence consistent with profitability expectations playing a central role. Following Aghion et al. (2023), we use inverse profit margins as a proxy for industry-country-year-level competition.[3] We find statistically significantly larger effects in markets with high levels of competition, in line with our model predictions for profit-oriented inventors. This highlights the importance of inventors' personal experiences in shaping profit expectations and ultimately affecting their innovation choices.

Our model predicts stronger responses in relatively larger green good markets, in line with the "building on the shoulders of giants" insight from the literature on market size and the direction of innovation (Acemoglu et al. 2012; Acemoglu et al. 2016), as well as research on innovation responses to market size more generally (Aghion et al. 2024). In larger markets, innovation becomes relatively cheaper because there is a richer base of existing knowledge on which to build.[4] We also take this to the data and find stronger effects of natural disaster exposure in product markets with larger green good shares.[5]

Related Literature & Contribution: Our central contribution is to causally identify personal experience as a driver of innovation. We highlight a novel channel: personal experiences influence inventors' profitability expectations. Disaster exposure shifts expectations about future green good demand and environmental regulation. It alters higher-order beliefs about consumers.

Our findings add to a small but growing literature that studies inventor-level drivers of innovation. Recent work has investigated how socioeconomic background affects who becomes an inventor, and documents unequal access to innovation careers (Aghion et al. 2017; Akcigit et al. 2017; Bell et al. 2019). There is also work that documents social and

[3]Our competition data come from CompNet (CompNet 2022).

[4]For example, inventing an induction stove is more feasible when the principles of magnetic induction are already well understood, reducing the cost and risk associated with developing new green technologies.

[5]We proxy for green good demand by the share of green goods in a product market, using data from PRODCOM and a list of green products from Bontadini and Vona (2023).

intrinsic motives to innovate (Stern 2004; Feng et al. 2021). Our work discusses inventors' personal experiences as central to their choice about what to innovate. These experiences affect inventors' choices through changes in their beliefs about the returns to innovation.

Our work builds on the behavioral experience effects literature, which documents correlations between personal experiences and household expectations about inflation, recessions, house prices, and stock returns (Malmendier and Nagel 2011; Malmendier and Nagel 2016; Kuchler and Zafar 2019; Laudenbach et al. 2023). Giuliano and Spilimbergo (2024) summarize this literature. We contribute to the literature on experience effects in three ways. First, we move beyond correlations and show that experience effects causally influence high-stakes decisions. Second, we extend the literature to the production side of the economy by showing that personal experiences affect innovation choices. Third, we disentangle the channels through which personal experiences operate, distinguishing intrinsic motivation from profit expectations.

Our findings relate to the literature on higher-order belief formation and salience. Evidence on higher-order belief formation has mostly been limited to experimental studies and information treatments in surveys (Coibion et al. 2021).[6] Our findings provide novel evidence from an observational setting on how personal experiences of large shocks shape higher-order beliefs. These findings also connect to the literature discussing the role of salience in decision making (Bordalo et al. 2012; Bordalo et al. 2022). Prior work related to natural disasters shows that they heighten local climate change salience and change voting and consumption patterns (Gallagher 2014; Herrnstadt and Muehlegger 2014; Djourelova et al. 2024; Chae et al. 2025). We show that inventors respond to these local changes, and that the salience of climate change affects high-stakes innovation decisions.

Lastly, we contribute to the literature on the determinants of the direction of innovation. Green R&D responds to market structure and policy incentives such as competition, energy-price shocks, and carbon regulation (Aghion et al. 2005; Acemoglu et al. 2012; Acemoglu et al. 2016; Hassler et al. 2012; Calel and Dechezleprêtre 2016). There is a small literature that links the invention of adaptation technologies such as drought-resistant crops and air-conditioning to natural disasters (Miao and Popp 2014; Barreca et al. 2016; Moscona and Sastry 2023). However, how innovation responds in the crucial domain of mitigation, technologies that directly combat climate change by reducing emissions, is poorly understood. We address this gap and show that natural disaster exposure leads to inventive activity that goes beyond damage control and targets forward-looking abatement. Our results show that

[6] Higher-order beliefs shape decision-making and coordination in markets. This layering of expectations helps explain diverse phenomena—from fluctuations in economic activity and asset price movements to behavioral distortions like myopia and anchoring (Lorenzoni 2009; Banerjee et al. 2009; Angeletos and Huo 2021; Huo and Takayama 2024).

there is an endogenous response to increasingly severe climate change, which integrated assessment models neglect (see for example Ackerman et al. 2009; Cai 2020). Crucially, this response depends on consumers' green preferences and the market environment.

The rest of this paper is organized as follows. Section 2 describes our data. Section 3 describes our empirical approach. Section 4 presents our results on patenting. Section 5 discusses our proposed mechanism and provides survey evidence on inventors updating their higher-order beliefs. Section 6 starts with our theoretical model and provides empirical evidence for our proposed comparative statics. Section 7 concludes.

2 Data

To conduct our analysis we draw on a variety of different data sources. Table 1 gives an overview of the data, the geographic coverage, the time period, and the key variables we use.

Table 1: Data Sources, Coverage, Periods, and Usage

Data & Source	**Countries**	**Time Period**	**Usage**
Patents (PATSTAT)	France, Germany (also data for EPO, USPTO, JPO)	1994–2014	Patent indicators; technology classification; inventor geolocations
Natural Disasters (EM-DAT & GDIS)	France, Germany	1980–2018	Location; severity; type
Firm-level Survey (Mannheim Innovation Panel)	Germany	2009, 2015, 2021	Firm-level green innovation measures; stated reasons for green innovation
Competition (CompNet)	France, Germany	From 2000	Industry-level competition measure (available years vary by country – see Appendix C.1)
Green Goods (Eurostat PRODCOM)	France, Germany	1995–2014	Industry-level production share of green products, green goods from Bontadini and Vona (2023)
Research Funding (ScanR)	France	1999–2023	Public research and innovation funding

2.1 Patents

To measure innovation, we use data on patent applications filed by inventors living in France and Germany from the European Patent Office's (EPO) PATSTAT database, covering the period from 1994 to 2014. Roughly 50% of patents filed at the EPO came from EPO member states. Of those, 50% came from France and Germany. They are the two most active countries among EPO member states in terms of patenting. We have additional information on research funding for France, and a firm-level survey on innovation for Germany. Hence, we focus our analysis on France and Germany.

Given our focus on the personal experiences of inventors rather than on patents themselves, it is crucial to have comprehensive data on inventors' patenting behavior regardless of where they choose to file these patents. Because we study inventors residing in France and Germany rather than patents filed solely within these countries, we require access to patent records extending beyond the European Patent Office (EPO). For example, a French inventor personally affected by a natural disaster may choose to patent an innovation in the United States, anticipating greater commercial potential there. PATSTAT meets this requirement by providing extensive data that includes filings not only at the EPO and its member states' national offices but also at global patent offices such as the Japanese Patent Office (JPO) and the United States Patent and Trademark Office (USPTO). Additionally, patents filed in these three jurisdictions—often referred to as triadic patents—are widely recognized indicators of high-value inventions (see, e.g., Dernis and Khan 2004; Rassenfosse and Pottelsberghe de la Potterie 2009; Dechezleprêtre et al. 2017).

We are interested in "green" technologies—innovations addressing climate change through mitigation or adaptation. To identify green patents, we rely on PATSTAT's Cooperative Patent Classification (CPC) data, an extended version of the International Patent Classification (IPC). CPC features the Y02 classification, explicitly denoting technologies designed for mitigating climate change effects or adapting to its impacts. Utilizing this classification, we distinguish between mitigation patents—those aimed at reducing the environmental impact of human activities—and adaptation patents—those designed to help societies better cope with climate change. The detailed CPC classes available in PATSTAT also allow us to categorize patents broadly into technological groups such as agriculture, concrete and cement making, or combustion engines. This detailed classification enables us to construct precise indicators representing a region's technological specialization. Figure 1 illustrates patenting activity from 1994 to 2014 in France and Germany, distinguishing green from non-green patents. Green patents comprise approximately 7.7% of all patents filed during this period, and this share gradually increased over time.

We supplement PATSTAT with detailed information on the location of inventors and applicants. Specifically, we use data from De Rassenfosse et al. (2019), which provides precise coordinates for each inventor's and applicant's primary place of residence at the time of patent filing. This data roughly corresponds to city-level assignments, enabling us to link all patents in our sample to the location of their inventors. The data are available up to

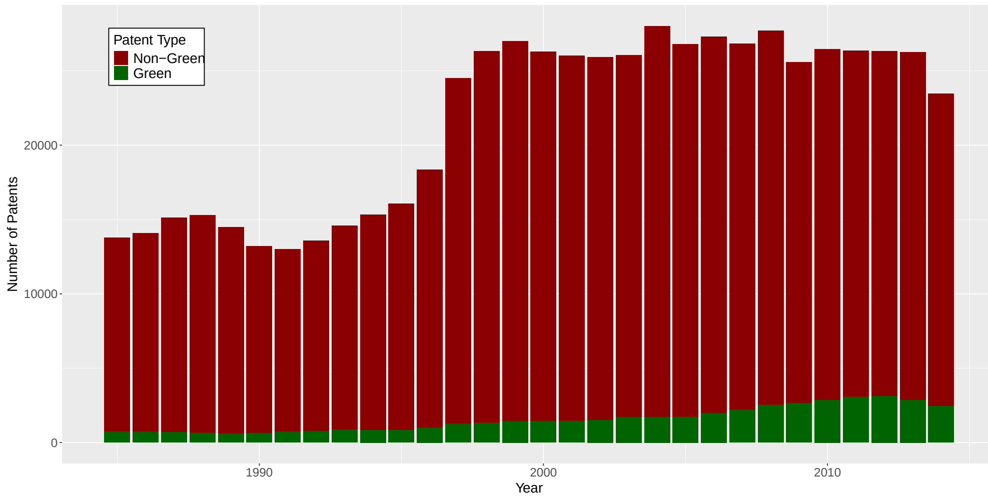


Figure 1: Patenting Activity in France and Germany over Time

Note: This figure depicts how patenting in France and Germany evolves over time until 2014. We split patents by green and non-green patents.

2014, limiting our analysis to years up to and including 2014.

From the available patent documents, we restrict our sample to first filings—i.e., the first time any application was made for a distinct invention within an EPO worldwide bibliographic data (DOCDB) simple patent family. All patents in a simple patent family are considered to cover the same technical content and share the same priority. In other words, they describe the same invention and represent the same technological advancement. A priority patent is the first patent filed for that specific invention. We use the priority date—the date of the first filing—as the year in which an invention was filed. Later claims or modifications to patent claims are excluded from our dataset, as we focus solely on original inventions. Thus, we do not count instances where an existing patent is subsequently filed in another jurisdiction. Similarly, we include only granted patents to ensure that what we measure is a true new invention.

2.2 Natural Disasters

We obtain information on natural disasters from the emergency events database (EM-DAT) published by the Centre for Research on the Epidemiology of Disasters (CRED) (see Guha-Sapir et al. 2022). In our analysis, we are interested in the emergence of innovations to combat and mitigate the consequences of climate change. We therefore only consider natural disasters that occur more frequently in France and Germany due to climate change: floods, storms, extreme temperature events, and droughts (see Intergovernmental Panel on Climate Change (IPCC) 2023). The CRED includes a disaster in the database if it meets at least one of the following conditions: (a) a death toll of ten or more people, (b) there are at least 100 people affected by the disaster, (c) the disaster causes the declaration of a state of emergency, or (d) the affected country calls for international assistance.[7]

We complement the EM-DAT data with geolocations from the Geocoded Disaster (GDIS) dataset (Rosvold and Buhaug 2021), which provides detailed spatial information on disasters from 1960 to 2018. GDIS assigns events to the most precise available administrative unit, ranging from national to subnational levels. In France and Germany, this includes up to three tiers of administrative divisions: régions and Länder (large federal or territorial states), départements and Regierungsbezirke (mid-level units akin to provinces), and arrondissements and Kreise (smallest administrative units, comparable to US counties). The arrondissement and Kreis levels correspond to the third Nomenclature of Territorial Units for Statistics (NUTS) level in France and the second NUTS level in Germany. There are 403 Kreise and 350 arrondissements in our data.

Until 1984, only a small number of disasters are geolocated below the first administrative level. We therefore only consider events from 1984 onward. For our event study, we use 10 years of lags and 4 years of leads, and use disaster data from the years 1984 to 2018. For our full sample, we end up with 150 distinct natural disasters, some of which affect multiple regions at once.

2.3 Analysis Sample - Patenting

We merge our patent and disaster data at the most granular administrative level in our data—arrondissements in France and Kreise in Germany. Throughout the analysis, we refer to this as the "regional" level or simply "region," which should not be confused with the French "région."

Our dataset includes approximately 520,000 patents, of which around 40,300 are classified as green. These patents were filed by approximately 1,385,000 and 110,000 inventors, respectively. On average, 33.8 patents are granted annually in each region, 2.6 of which are green patents. We aggregate all patents by the region of their inventors. Since some patents have multiple inventors with addresses in different administrative areas, we assign each region a proportionate share of the patent. For instance, consider a patent i with three inventors: $1, 2, 3$, where two live in Region A and one in Region B. Patent P would then be attributed with a share of $2/3$ to Region A and $1/3$ to Region B. More generally, to calculate the count of all green patents in region l in year t, we sum over all patents i, weighting by the share of i's inventors residing in region l:

[7] See `https://doc.emdat.be/docs/protocols/entry-criteria/` for the precise inclusion criteria.

$$C(\mathbf{Y02}_{lt}) = \sum_{i}^{N} \left(\frac{[\mathbf{Y02}_{ilt} = 1]}{\sum_{l}^{L} [\mathbf{Y02}_{ilt} = 1]} \right) \tag{1}$$

where

$$[\mathbf{Y02}_{ilt} = 1] = \begin{cases} 1, & \text{if patent } i \text{ in year } t \text{ and region } l \text{ is green (Y02)} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

This yields a continuous (in fraction of counts) variable for the annual number of green and non-green patents in each region. To ensure comparability between green and non-green patents, we normalize the count of each type of patent in each region by its respective mean across all years t and all regions l:

$$P(\mathbf{Y02}_{lt}) = \frac{C(\mathbf{Y02}_{lt})}{\frac{1}{L} \sum_{l}^{L} \frac{1}{T} \sum_{t}^{T} C(\mathbf{Y02}_{lt})} \tag{3}$$

where L is the number of regions and T is the number of years, and equivalently for non-green patents. We adopt the same normalization procedure when aggregating across subclasses or when splitting the sample by e.g. competition.

Natural disasters are reported at either the first-, second-, or third-order administrative level. To ensure consistent spatial coverage, we assign each disaster reported at the first- or second-order level to all corresponding third-order areas within the respective administrative boundary. For instance, if an extreme temperature event is reported in the German state Hessen, all 26 Kreise within Hessen are coded as being exposed during this period. Our sample includes 150 natural disasters in total. Broken down by type, there are 64 floods, 63 storms, 20 extreme temperature events, and 3 droughts.

Figure 2 visualizes the geographic variation in both disaster exposure and green patenting activity across the regions in our sample. Regions shaded in yellow are characterized by elevated levels of green patenting but relatively few natural disasters, while those shaded in blue have experienced many disasters but exhibit limited green innovation. Green-shaded regions display both high disaster exposure and high green patenting, indicating potential alignment between environmental shocks and green innovation. In contrast, gray areas denote regions with neither significant disaster exposure nor notable green patenting activity.

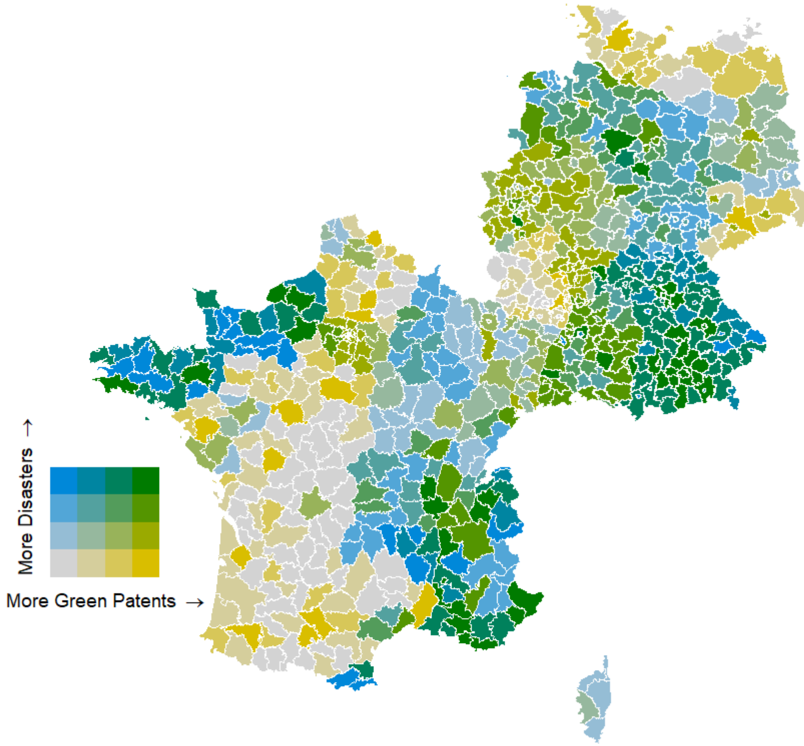


Figure 2: Bivariate Map of Green Patent and Disaster Counts

Note: This map depicts the bivariate variation in green patenting (shades of yellow) and natural disasters (shades of blue). Darker tones signify more patents (disasters) respectively. Shades of green indicate regions with high levels of both green patents and natural disasters. Grey regions have a very low number of patents and disasters. Only green patents are displayed and we pool all years.

3 Empirical Strategy

This section outlines our empirical strategy for estimating the effect of natural disasters on innovation. Innovation is a gradual process: the path from idea to patentable prototype often spans years. To capture these dynamics, we adopt an event-study design, which allows us to observe the dynamics of patenting following a natural disaster. Our baseline event-study specification, applied to the data, is presented in the equation:

$$P(\mathbf{Y02}_{lt}) = \sum_{s=-5, s\neq -1}^{11} \beta_s D^s_{l,t} + \gamma_1 CPC_{lt} + \lambda_{c(l),t} + \lambda_l + \epsilon_{lt} \tag{4}$$

with

$$D^s_{l,t} = \begin{cases} \sum_{s=-\infty}^{-5} d_{l,t-s} & \text{if } s = -5 \\ d_{l,t-s} & \text{if } -5 < s < 11 \\ \sum_{s=11}^{\infty} d_{l,t-s} & \text{if } s = 11 \end{cases} \tag{5}$$

where $P(\mathbf{Y02}_{lt})$ is the normalized count of patents (as specified in equation (3)), and $d_{l,t-s}$ is the count of natural disasters experienced by region l in year $t-s$. The reference period is the year prior to disaster exposure. Following McCrary (2007) and the formal definition of Schmidheiny and Siegloch (2023), we bin all periods that are more than 10 years in the past or more than 4 years in the future. We include region fixed effects λ_l and country-by-year fixed effects $\lambda_{c(l),t}$, where $c(l)$ denotes the country that region l belongs to. CPC_{lt} is a vector of controls representing a region's innovation composition at time t. For every region, we calculate the percentage of patents falling into a broad CPC class.[8] These controls allow us to account for different time trends in a region's patenting industry composition. For instance, we can account for the impact of a large pharmaceutical company, which frequently patents, leaving a region, which would affect patenting in class C - "Chemistry; Metallurgy".

Region level fixed effects (λ_l) control for region-specific natural disaster risk characteristics and account for differences, such as one region being more accustomed to floods than another. Although the exact timing of natural disasters is random, some regions experience such events more frequently, as shown in Figure 2: coastal and Alpine areas face higher disaster risks than interior regions. Inventors might choose locations based on these regional risks, potentially causing selection bias. Region fixed effects mitigate this concern by capturing region-specific disaster exposure and institutional characteristics that are constant over time. Additionally, country-by-year fixed effects ($\lambda_{c(l),t}$) account for trends in overall disaster risk and differing innovation patterns between France and Germany.

Our coefficients of interest, β_s, estimate the average change in green innovation in a region at event time s, relative to the year before the disaster ($s = -1$), controlling for time-invariant regional characteristics and differential trends across countries. Identification comes from cross-regional variation in disaster timing. Because our natural disaster data are only available at the regional level, our estimates resemble an intent-to-treat effect. If a flood impacts only part of a region—such as a valley—we still treat all inventors in that region as exposed. This likely attenuates the estimated effect and yields a conservative lower bound on the individual-level response. We cluster standard errors at the regional level, which is the level of treatment variation.

One remaining identification concern is that climate change may induce differential trends in underlying disaster risk across regions. If these trends are observable to inventors, they may select into regions accordingly, generating potential selection bias based on heterogeneous regional risk trajectories. We argue that the absence of such selection is plausible in

[8] These classes are: A - "Human Necessities - Agriculture", B - "Performing Operations; Transporting", C - "Chemistry; Metallurgy", D - "Textiles; Paper", E - "Fixed Constructions", F - "Mechanical Engineering; Lighting; Heating; Weapons; Blasting", G - "Physics", H - "Electricity". For example, in 2007, 33% of all patented inventions by inventors in Dunkerque had the CPC class C (Chemistry; Metallurgy).

our setting, as the regional impact of climate change is inherently difficult to predict, even for climate scientists (Hulme et al. 1999). Moreover, the literature on migration patterns following natural disasters mostly documents out-migration of skilled individuals (Boustan et al. 2020), and inventors are highly skilled (Bell et al. 2019). If out-migration of inventors occurred in our setting, our estimates would be biased downward and suffer from attenuation. If the opposite was true, and inventors moved to affected regions, we would overestimate the effect. The underlying assumption of our work is that inventors do not select into regions based on regional differences in the trend of natural disasters.

We observe the universe of patent applications, which allows us to identify a subset of inventors who previously filed in the same region. In Section 4.5, we show that our results remain robust when restricting to this subsample (see Figure 6b), which alleviates concerns about inventor selection. A remaining caveat is that we observe inventors only at the time of filing, so unobserved moves between filings cannot be entirely ruled out—even for apparent stayers. Additionally, in Section 4.7, we show that self-reported climate change affectedness is robustly correlated with our natural disaster measure.

In our context, the stable unit treatment value assumption (SUTVA) implies that there are no unmodeled spillovers between regions. We will later explicitly model spillovers to neighboring regions and show that natural disaster exposure only marginally affects directly adjacent regions.[9]

A concern in our event study framework is the potential presence of heterogeneous treatment effects. Standard two-way fixed effects (TWFE) estimators, as used in our baseline specification, implicitly average treatment effects across groups that may differ in the timing and magnitude of treatment, potentially leading to biased or misleading estimates when treatment effects are heterogeneous. In our setting, regions are exposed to different numbers of disasters at different points in time, and the effect of an additional disaster may vary depending on prior exposure. This dynamic poses a challenge: regions used as controls at a given point may themselves become treated in subsequent periods, and their treatment effects may not be comparable to the newly treated units.

To address this concern, in Section B.1 of the Online Appendix we adopt the estimator proposed by Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024). This estimator constructs control the group by conditioning on treatment history. Specifically, regions that have experienced the same cumulative number of disasters up to $t-1$ form the control group, and those newly treated at t are compared against those that remain untreated at that time. Over time, as more units receive treatment, the control group shrinks.

[9]The effect is 1/8 of our baseline estimate for the effect on the directly exposed region. See section 4.2 for our results on spillovers. In general, positive spillovers would mean attenuation of our baseline estimates.

Our baseline model on the other hand, maintains a fixed control group. While the alternative estimator yields somewhat larger and more persistent effects (Figure B.1 in Section B.1 in the Online Appendix), the results are qualitatively consistent with those from our preferred TWFE specification (Figure 3 in Section 4). This robustness across estimation strategies provides reassurance that our main findings are not driven by bias due to heterogeneous treatment effects, even if each approach carries its own limitations. We mainly report the TWFE results because they provide more conservative estimates, and also potentially offer greater external validity due to a more realistic and stable control group.

We are also interested in the long-run average effect that one additional disaster has on green innovation in a region l. To estimate this effect, we use the following collapsed difference-in-differences equation:

$$P(\mathbf{Y02}_{lt}) = \beta \left(\sum_{s=0}^{\infty} d_{l,t-s} \right) + \gamma_1 CPC_{lt} + \gamma_2 \lambda_{c(l),t} + \gamma_3 \lambda_l + \epsilon_{lt}, \tag{6}$$

where $\sum_{s=0}^{\infty} d_{l,t-s}$ represents the cumulative number of past natural disasters. The parameter of interest, β, estimates the average effect that one additional disaster has on the number of green patents in a region.

To summarize, our identifying variation comes from the random timing of severe natural disasters across regions, which—conditional on regional fixed effects—is plausibly exogenous and allows us to compare changes in green innovation in affected regions before and after disasters relative to unaffected regions. Our data contain only severe natural disasters. Therefore, we caution that not all exposure to the forces of nature induces changes in inventor behavior.

4 Effects on Innovation

Figure 3 presents our results when estimating our event-study specification (4) for green and non-green innovation. Year 0 represents the partially treated year.[10] While the initial effect is small, we observe a large and significant impact two years after the natural disaster, with the effect peaking five years after the event. Five years after natural disaster exposure, green patenting is 24% higher than in unaffected regions. Subsequently, the effect diminishes over time, becoming insignificant ten years after the natural disaster. We interpret the inverted U-shape of the innovation response as stemming from the fact that innovation takes time. Natural disasters trigger an impulse towards inventive activity, with the resulting innovations

[10] If region l experienced a natural disaster in June, only patents filed in the months after could potentially be influenced by the natural disaster.

materializing in the subsequent years. This pattern aligns with earlier literature, which suggests that the salience and behavioral response to natural disaster exposure tend to fade over time (see Gallagher 2014). The initial lag is consistent with innovation taking time.

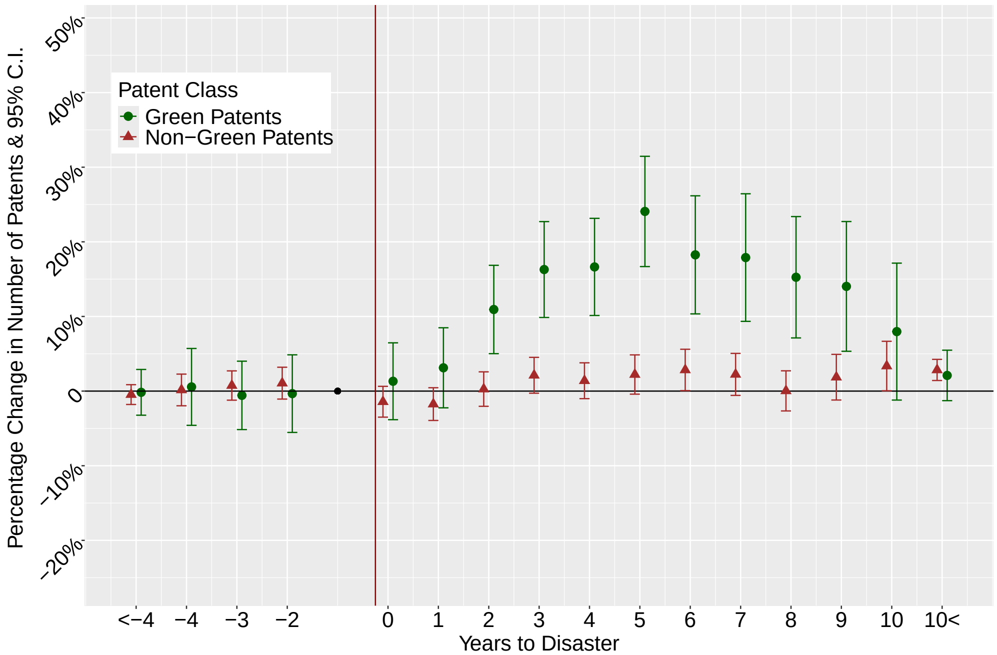


Figure 3: Patenting following the Exposure to a Natural Disaster

Note: This figure depicts the results for our baseline event-study specification, where we compare patenting in regions exposed to natural disasters to unaffected regions. We plot two separate regressions for green and non-green patents. Percentages are relative to the overall sample averages of green/non-green patents per year per region: (2.54) and (30.5) respectively. An increase in green patenting of 24% corresponds to 0.61 additional green patents. Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

We find no significant change in non-green innovation, consistent with limited crowding out of other inventive activity. The magnitude of our effects is substantial. In comparison, Calel and Dechezleprêtre (2016) find a 10% increase in green patents among firms covered by the EU Emissions Trading System (EU-ETS) in its early years, using the same measure of green innovation we employ. Relative to their estimates, we observe a larger short-run spike in patenting five years after a disaster, while our long-run effect, an 8.2% increase relative to the sample average (Table 2), is of similar magnitude but slightly smaller. Similarly, the oil crisis led to a 3% rise in green patenting (Popp 2002; Hassler et al. 2012), and a 10% increase in fuel prices generated a 10% increase in green innovation (Aghion et al. 2016). By this benchmark, natural disasters elicit a large and statistically significant response from local inventors. That said, comparisons should be interpreted cautiously: while policy shocks like the EU-ETS or oil price spikes are often systemic and partly predictable, natural disasters are inherently local and unpredictable.

The event study plots indicate flat pre-trends, with pre-treatment coefficients closely centered around zero, supporting the validity of the parallel trends assumption. To address concerns about heterogeneous treatment effects, in Section B.1 we re-estimate our main green innovation results using the estimator proposed by Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024).

In Section B.3 of the Online Appendix, we show that our results are consistent across a broad range of CPC classes and are not driven by any single technological domain. To assess this, we replicate our baseline specification separately for green patents grouped by the broad CPC class they belong to, based on the primary technology classification of each patent. The post-disaster response is remarkably similar across classes B (Performing Operations; Transporting), C (Chemistry; Metallurgy), F (Mechanical Engineering; Lighting; Heating), G (Physics), and H (Electricity). The effects are more volatile in D (Textiles; Paper) and E (Fixed Constructions), while in A (Human Necessities)—which includes agriculture—the response is comparatively weak or absent. Throughout, we control for a region's broad patenting composition. However, this composition may itself be endogenous to natural disaster exposure. In Section B.2 of the online Appendix, we demonstrate that our results remain robust and nearly identical when we omit these technology trend controls.

4.1 Mitigation vs. Adaptation

Do inventors primarily adapt to a changing environment (see, for instance, Miao and Popp 2014 and Moscona and Sastry 2023), or do their inventions combat the causes of climate change? We investigate this by exploring the subcategories of green patents.

We split the sample of green patents based on their purpose—either to adapt to climate change or to mitigate climate change. Specifically, we use the Y02A class, "technologies for adaptation to climate change," and all the other Y02 subclasses which relate to mitigation. Mitigation technologies for climate change are inventions that reduce greenhouse gas emissions or enhance carbon removal from the atmosphere. Examples include renewable energy (like solar and wind), electric vehicles, carbon capture and storage, and energy-efficient buildings.[11] Table 2 presents the estimates for our difference-in-differences specification (6).

In the long run, one additional natural disaster increases patenting in mitigation technologies by 8.6% compared to the sample average, and patenting in adaptation technologies by 4.4%. Mitigation technologies are crucial in order to reduce long-run emissions. These coefficients are also statistically significantly different.[12] There are roughly 10 times more mitigation patents than adaptation patents in our sample. Section B.4 of the Online Appendix presents our results when estimating our event-study specification. We find that the

[11]See Online Appendix Section B.4 for an overview of all the Y02 classes used in this analysis.

[12]Using a Wald-test, we test whether these coefficients are statistically significantly different and can reject the null hypothesis of equality with a p-value of 0.0097.

pattern for mitigation patents largely mirrors our main results, while the effect on adaptation technologies is comparatively muted.

Table 2: Patenting Responses split by Adaptation vs. Mitigation

	Dependent variable:		
	All Green	Mitigation	Adaptation
	(1)	(2)	(3)
Cumulative Count	0.082***	0.086***	0.044***
	(0.009)	(0.010)	(0.013)
Country-Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes
Wald-test p-value		0.0097***	
Sample Mean	2.54	2.32	0.22
Observations	15,813	15,813	15,813
R^2	0.739	0.723	0.513
Adj. R^2	0.725	0.708	0.487

Note: This table gives the results for our baseline regression for all green patents (1), and split by mitigation and adaptation in columns (2) and (3). Cumulative Count is the count of past natural disasters. We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})^2}{\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})}$, where: $\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}}) = \text{Var}(\hat{\beta}_{\text{eq1}}) + \text{Var}(\hat{\beta}_{\text{eq2}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq1}}, \hat{\beta}_{\text{eq2}})$. We can reject the Null hypothesis $H_0 : \beta_{\text{eq1}} = \beta_{\text{eq2}}$ against the alternative $(H_1 : \beta_{\text{eq1}} \neq \beta_{\text{eq2}})$ with the reported p value. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

Inventors thus not only invent technologies protecting against the adverse effects of climate change, but they patent ideas that help combat climate change itself. Mitigation technologies are not directly tied to natural disasters. The strong effects we observe for these technologies suggest that inventors respond not only to the immediate threat of disasters, but also by developing innovations with broader applications in everyday products. This implies that they not only recognize rising risks, such as increased flood frequency, but also perceive greater value in technologies that reduce GHG emissions. In Section 5, we show that these expectations about greater value, at least in part, stem from inventors' higher-order beliefs about consumer preferences about green consumption and environmental policy.

In Online Appendix Section B.4, we additionally present results for all the subclasses in isolation. Estimating our baseline difference-in-differences specification (6) separately for each of these subclasses, we find that the coefficient on the cumulative count of past disasters is consistently positive and statistically significant across all subclasses. Of particular interest for mitigation are the Y02E class, "reduction of greenhouse gas (GHG) emissions related to energy generation, transmission, or distribution," and the Y02T class, "climate change mitigation technologies related to transportation," as they cover the most polluting activities. Additionally, we present event study estimates for these two subclasses separately. The patterns mirror our main results, emphasizing that inventors react across different industries—even in the most polluting ones.

4.2 Spillovers

If personal experience is the primary channel through which natural disasters affect innovation, then we should observe little to no impact in neighboring regions that were not directly exposed. To test this, we examine potential spillovers by estimating the effect of disaster exposure in adjacent regions on local patenting activity. For each region, we calculate the number of natural disasters in neighboring regions. Figure 4 depicts our different distance bands within which we consider a region to be a neighbor. Put differently, we estimate the effect of natural disasters in the black-shaded region on patenting in neighboring regions. Red-shaded areas are regions whose borders are closer than 50km, while orange-shaded areas are closer than 100km away, and yellow shaded areas are closer than 150km away. To avoid including exposed regions in the control group, we remove all regions that experienced natural disasters in the past five years.

We estimate our difference-in-differences specification (6) and depict the results in Table 3. Natural disasters only marginally affect patenting in directly adjacent regions, leading to a long-run increase in patenting of about 1% in adjacent regions. Relative to the results presented in Table 2, the magnitude of the increase is approximately eight times smaller. When we move to regions that are 100km or 150km away, we find precisely estimated point estimates close to zero. There is no sizeable effect of natural disasters on regions that are more than 50km away. The lack of large spillovers is striking and underlines that the direct personal experience of the inventor is the driving force behind our results.

While our approach of excluding affected regions from the control group ensures clean identification, it also systematically excludes regions that experience disasters more frequently. This exclusion may introduce some bias, as effects are primarily identified from regions with lower disaster exposure. In section B.7 in the Online Appendix, we also show our results when we exclude regions that have been affected in the past three, four, six, seven years respectively. We also have one specification where we include all affected regions in the control group, thus not restricting our sample. Results are qualitatively the same for both

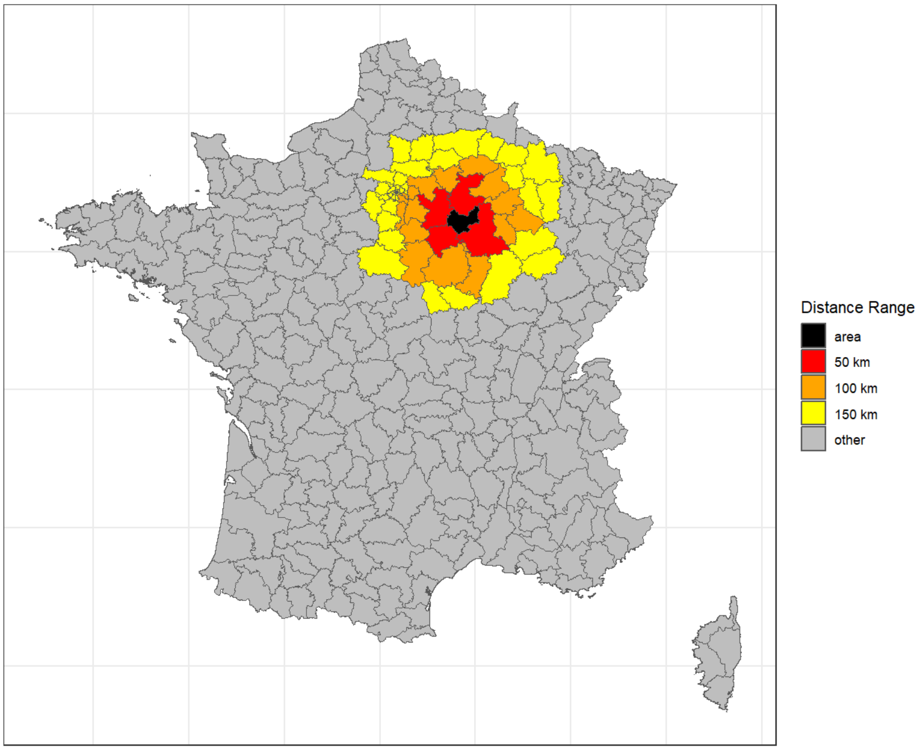


Figure 4: Illustration of Distances to Region

Note: This figure depicts the different distances at which we consider an area to be a neighbor of the black-shaded region in the center. Red-shaded areas are regions whose borders are closer than 50km to the area of interest, while orange-shaded areas are closer than 100km away, and yellow-shaded areas are closer than 150km away. We show only France for simplicity.

types of robustness checks.[13]

4.3 Patent Value

To assess whether natural disaster exposure spurs economically valuable innovation, we examine the value of resulting patents. A key concern is that observed increases in patenting may reflect low-quality or hastily conceived inventions. To address this, we use citation counts, a proxy for patent value, to gauge the technological and commercial relevance of disaster-induced innovations. Prior work shows that more highly cited patents are more socially valuable (Trajtenberg 1990), command higher market valuations (Hall et al. 2005), and are more likely to be sold (Harhoff et al. 1999). More recent studies further affirm their reliability as indicators of patent quality (Jaffe and Rassenfosse 2017).

[13] When we exclude all regions affected in the past six, and seven years, we find slightly larger and more imprecise estimates for the 50km range. When we do not restrict the control group, the results remain very similar for the 50km range. We find very small but significant negative effects of neighboring natural disasters that are more than 50km away. This is due to the control group now containing regions that are affected by natural disasters. We essentially invert our main regression. In this specification, we compare an area unaffected by a natural disaster with areas that are affected.

Table 3: Spillovers of Neighboring Disasters

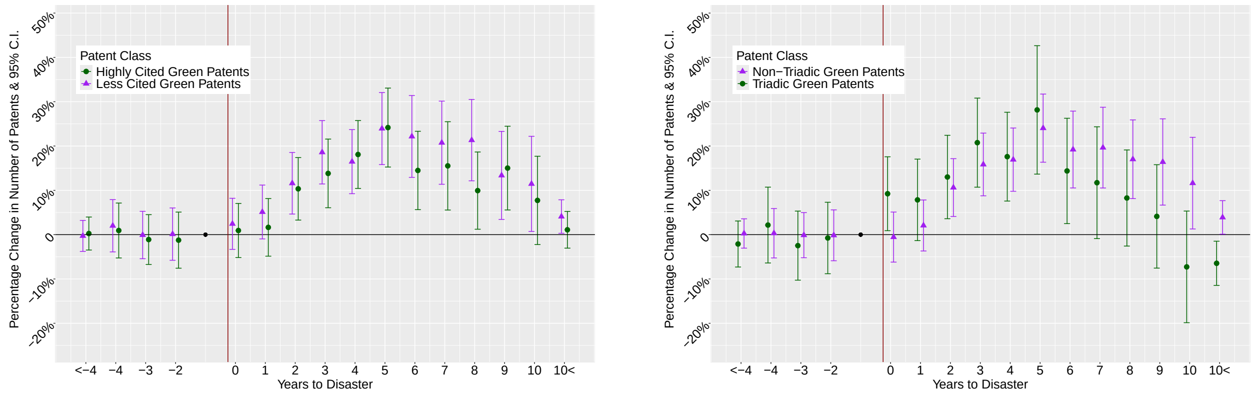
	Dependent variable:		
	$P(Y02_{lt})$		
	(1)	(2)	(3)
Cumulative Count (50km) Neighboring Disasters	0.0100^{***} (0.0037)		
Cumulative Count (100km) Neighboring Disasters		0.0001 (0.0005)	
Cumulative Count (150km) Neighboring Disasters			-0.0005 (0.0004)
Country-Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes
Observations	4,125	4,125	4,125
R^2	0.8499	0.8493	0.8494
Adjusted R^2	0.8201	0.8193	0.8194

Note: This table shows our regressions results for spillovers from adjacent regions. "Cumulative Count Neighboring Disasters" is the count of past natural disasters in neighboring regions. Which regions are considered as "neighbors" depends on the distance threshold as shown in Figure 4. From these regressions, we exclude all regions that themselves experienced a disaster in the past 5 years. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

We investigate whether our findings result from the invention of high- and/or low-value patents by examining the effects for patents with high and low citation counts separately. We split the sample based on patents that received citations above or below the median within their respective groups. Given that a patent published in 1995 is likely to have more citations than one published in 2005, and that a patent for a toothbrush may attract a different number of citations compared to one on quantum computing, we compare patents within the same CPC class j (e.g., CPC class C for Chemistry) and published in the same year t. Let the group of patents belonging to CPC class j published in year t be denoted by G_{jt}. For all such groups, we then compute the median number of citations, denoted by $\tilde{G}_{jt}$. Since a patent might belong to multiple CPC classes (for instance, j and k), we define it as having above-median citations if:

$$\text{Citations}_{it} > \frac{\tilde{G}_{jt} + \tilde{G}_{kt}}{2}. \tag{7}$$

Figure 5a plots the results when estimating our event-study (4) for both samples.



(a) Patenting Activity by Citation

(b) Triadic vs Non-Triadic Patenting

Figure 5: Green innovation response to natural disaster exposure by patent characteristics

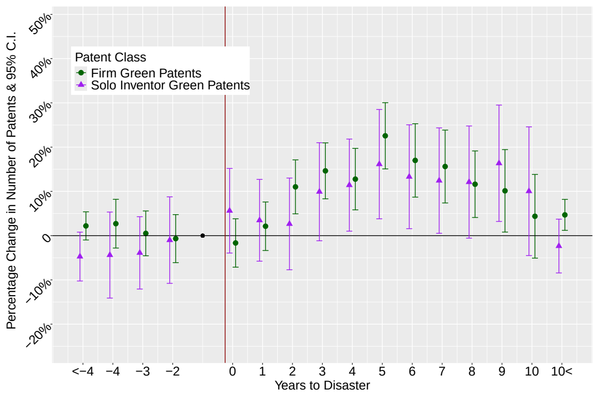
Note: This figure presents results from our event-study analysis of green patenting following natural disasters, split by different patent characteristics. Panel (a) differentiates patents by citations (above vs below median citations), with a sample mean of 1.271 (highly cited) and 1.253 (less cited) green patents per region-year. Panel (b) differentiates between Triadic and Non-Triadic green patents, with sample means of 0.503 and 2.05, respectively. Standard errors are clustered at the region level, and confidence intervals represent the 95% confidence level.

Both regressions show a positive, significant effect on subsequent green patents, as observed in our baseline results in Figure 3. Moreover, there does not seem to be a significant difference between patents with different citation counts. Our results suggest that natural disasters stimulate patenting activity regardless of whether patents are highly cited or not, indicating broad-based innovation rather than targeted low-value activity.

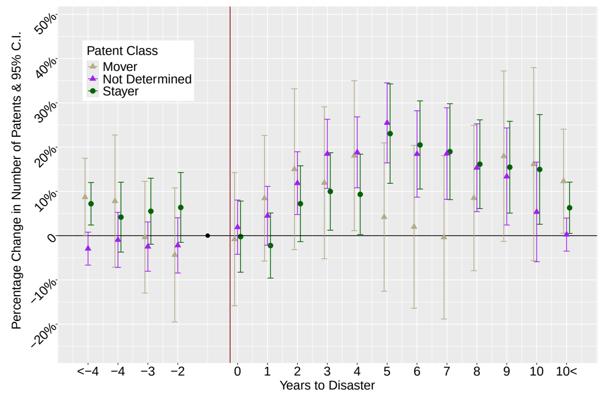
Another commonly used way to measure patent value is whether patents belong to a triadic family. A triadic patent is a patent filed at the European Patent Office (EPO), the Japanese Patent Office (JPO), and the United States Patent and Trademark Office (USPTO). Patents of such nature are usually quite valuable, as filing multiple patents in vastly different jurisdictions is, first of all, expensive, and secondly, implies that their technical content is economically valuable in some of the biggest markets on earth. We then use this indicator to estimate our event study for these triadic patents. Figure 5b plots our results. We find a similar pattern as in our baseline regression. Significant effects on triadic patents highlight that local experiences generate innovations with global market relevance, showing that inventors' responses are economically substantive and internationally applicable. As triadic patents are filed all over the world, these findings also alleviate the concern that our results are driven by any effect the natural disaster might have on the patent examiner. It is unlikely that a disaster in the south of France will influence the examiner at the USPTO.

4.4 Types of Inventors

To better understand who drives the observed green innovation response to natural disasters, we disaggregate our analysis by inventor type, using detailed information on applicants and inventors recorded in PATSTAT. This is possible because PATSTAT includes standardized names for both inventors and applicants, along with information on applicant type—such as whether the applicant is a firm or an individual.[14] In our sample, 72% of patents are filed by firms and 16.8% by individual inventors. For the remaining 11.2%, the applicant type cannot be determined.[15]



(a) Firms vs Individual Inventors



(b) Stayers vs Movers vs Not Categorized

Figure 6: Innovation by Inventor Type and Mobility

Note: This figure presents results from our event-study analysis of green patenting following natural disasters, split by inventor characteristics. Panel (a) differentiates patents filed by firms (sample average: 1.82 patents per region-year) and solo inventors (sample average: 0.43 patents per region-year). Panel (b) differentiates inventors by their mobility status: Stayers (sample average: 0.58), Movers (sample average: 0.1), and Not Determined (sample average: 1.86). Standard errors are clustered at the region level, and confidence intervals represent the 95% confidence level.

We estimate equation (4) separately by inventor type, using the count of all patents filed by either firms or individuals as the outcome. As patents can be filed by an individual and a firm jointly, when focusing on individual patent holders, we only keep patents exclusively filed by individuals. We compare the patenting behavior of exposed and unexposed inventors, separately for those affiliated with firms and those working independently. Figure 6a shows the event-study results. Given the larger number of patents filed by firms, estimates for firms are more precise. Natural disasters affect both inventors embedded in firms and those working independently or in small teams.

In Section B.12 of the Online Appendix, we show that personal experience of natural disasters increases green patenting along both the intensive and extensive margins, affecting both first-time and repeat inventors. We classify an inventor as a repeat inventor when they have previously shown up as an inventor in the patent system. Any inventor that files additional patents only afterward or only once is classified as a first-time inventor. We classify a patent as coming from a repeat inventor if at least one of its inventors has previously patented. Notice that the majority (roughly 83%) of patents are filed by at least one repeat

[14]This classification in PATSTAT is based on data from ECOOM (K.U. Leuven).
[15]We omit results for this unclassified group.

inventors. Both first-time and repeat inventors react to natural disaster exposure, with the response being significantly larger among repeat inventors.

In Online Appendix Section B.13, we further explore how inventors' past patenting activities influence their innovation response to natural disasters. Specifically, we differentiate between inventors with extensive prior patent filings ("large filers") and those with fewer previous patents ("small filers"), additionally distinguishing between inventors with substantial past engagement in environmentally harmful ("brown") technologies versus those with less or no prior involvement. Overall, the observed innovation responses are relatively similar across these classifications; however, large patent filers consistently exhibit stronger responses than small patent filers.

4.5 Inventor Movement

To address potential concerns about endogenous inventor selection, we examine whether green innovation responses differ between inventors who remain in their region and those who move. For a limited sub-sample of inventors, we know if they were previously recorded as living in the same region, or if they have moved. We can thus compare the evolution of patents for inventors who either stayed, moved, or for whom we do not have such information. We know that roughly 23% of inventors did not move, 4% moved, and we lack information to pinpoint the moving status for the rest (63%). Figure 6b plots our results. For inventors who did not move, results remain similar to our baseline findings. Results are noisy for movers, likely because we have limited statistical power due to the low number of movers in our sample. For those inventors for which we cannot determine their status, results are very similar to our baseline findings. Our findings alleviate some of the concerns about inventor selection into affected regions, as inventors who did not move equally respond to natural disaster exposure.

4.6 Disaster Severity

To explore whether the magnitude of natural disasters shapes the innovation response, we examine how green patenting varies with disaster severity, distinguishing between more and less deadly events as well as more and less economically damaging ones. Table 4 presents estimates from our baseline difference-in-differences specification (6), comparing the effects of natural disasters on green innovation separately by disaster severity. In columns (1) and (2), we contrast the effects of disasters with death tolls above the median column (1) and economic damages above the median column (2) to those with lower severity.

Previous work has shown that disasters involving significant loss of life create greater

Table 4: Patenting Effects by Disaster Severity

	$P(Y02_{lt})$	
	Split by Median	
	Deaths	Damages
	(1)	(2)
Cumulative Count: Above Median	0.1074***	0.0582*
Most Severe Disasters	(0.0179)	(0.0298)
Cumulative Count: Below Median	0.0564**	0.0868***
Less Severe Disasters	(0.0225)	(0.0115)
Country-Year F.E.	Yes	Yes
Region F.E.	Yes	Yes
CPC Controls	Yes	Yes
P-Value: Coef. Difference	0.1627	0.4282
Observations	15,813	15,813
R^2	0.7386	0.7386
Adjusted R^2	0.7247	0.7246

Note: This table compares disasters with above and below median level disaster severity as measured by either deaths or damages. In Column (1) disasters are split along the median on to their number of deaths. In column (2) disasters are split along the median on the monetary value of damages. We test for difference in coefficients between severe and less severe disasters using a Wald test of the form $W = \frac{(\hat{\beta}_{\text{top}} - \hat{\beta}_{\text{bot}})^2}{\text{Var}(\hat{\beta}_{\text{top}} - \hat{\beta}_{\text{bot}})}$, where $\text{Var}(\hat{\beta}_{\text{top}} - \hat{\beta}_{\text{bot}}) = \text{Var}(\hat{\beta}_{\text{top}}) + \text{Var}(\hat{\beta}_{\text{bot}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{top}}, \hat{\beta}_{\text{bot}})$. We test the null hypothesis $H_0 : \beta_{\text{top}} = \beta_{\text{bot}}$ against the two-sided alternative $H_1 : \beta_{\text{top}} \neq \beta_{\text{bot}}$, and report the corresponding p-value. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

salience of climate-related risks among the public (Eisensee and Strömberg 2007; Kalatzi Pantera et al. 2023; Demski et al. 2017). We find that highly deadly disasters have stronger effects on green innovation compared to less deadly disasters. This is in line with our proposed mechanism, as larger increases in public salience of climate change should translate into inventors forming higher monetary expectations, thereby prompting a stronger innovation response.[16]

In contrast, our analysis of economically damaging disasters shows weaker innovation responses for the most severe disasters. In column (2), the effect for the most damaging disasters is smaller that that for the less destructive disasters. This result is in line with literature documenting that large-scale economic disruptions from disasters destroy productive

[16]We also examine the effects of the single most severe disaster experienced by a region, which yields larger but statistically noisier coefficients. These results are reported in Section B.5 of the Online Appendix. In addition, we explore heterogeneity by disaster type. Due to the small number of drought events in our data (only three cases), we exclude them from this analysis. For extreme temperature events, floods, and storms, we find positive effects on green innovation that broadly mirror the patterns shown in Figure 3, albeit with greater noise. Results are reported in Section B.6 of the Online Appendix.

capital and critical infrastructure, which may in turn impede innovation by limiting firms' capacity to invest and adapt (see Peters et al. 2024; Le et al. 2024).

4.7 Survey Measure of Green Innovation

Patent data are frequently used to measure innovation; however, there are some limitations e.g. not all innovations are patentable, and not all inventors opt to patent their innovations. To further underline our findings, we repeat our analysis using an alternative indicator for green innovation based on survey data from the German part of the Community Innovation Survey (CIS), a biennial firm-level survey covering innovation activity. While exclusively focusing on firms is a drawback, the majority of green innovation occurs within a firm structure: approximately 72% of patents in our data are filed by inventors embedded within firms, compared to only 16.8% filed by individuals.[17] The core questionnaire of the CIS captures general innovation behavior, selected waves also include a dedicated module on environmental innovation. These green innovation questions were introduced in 2009 and repeated in 2015 and 2021. Survey responses are provided by individuals within firms who are familiar with the innovation process or directly involved in R&D. However, because we did not conduct the survey ourselves and the CIS does not record respondent identifiers or roles, we cannot observe who exactly within the firm completed the questionnaire. Our analysis sample comprises 18,425 firm-year observations from these three survey waves. The CIS is structured as a repeated cross-section, and firms cannot be tracked across waves due to the absence of consistent firm identifiers. The CIS contains region-level information of the firms' location, which we use to link firms to our natural disaster data.

We construct three alternative indicators of green innovation. The first captures the implementation of internal environmental innovations within firms, such as technologies that reduce energy, material, or water use, lower emissions or pollution, substitute fossil fuels with renewables, or introduce safer materials. On average, 48.3% of firms report the adoption of such internal green processes. The second indicator focuses on the introduction of new or significantly improved products or services offering environmental benefits—such as facilitating recycling, reducing pollution, or extending product life. On average, 34.8% of firms report such product- or service-based green innovations. Both of these are dummies that are equal to one if a firm indicated that they introduced one of these innovations. The third measure combines both indicators.[18]

[17] For the remaining 11.2%, we are unable to determine the type of inventor. See Section 4.4 for details on how inventor types are classified.

[18] Section B.9 in the Online Appendix describes the exact procedure how we construct our different measures for green innovation.

In Table 5 (columns 1-3), we regress all three indicators of green innovation on the count of past natural disasters. One additional past natural disaster increases the likelihood of introducing process innovation and green products by roughly 4.3% and 4.7%, respectively.[19] The analysis supports our prior findings and highlights the positive and significant effect of natural disaster exposure on green innovation. We do robustness checks in Section B.9 in the Online Appendix, where we include NUTS-2 and region-level (NUTS-3) fixed effects. Results remain robust with NUTS-2 fixed effects. With region-level fixed effects, point estimates are similar but lose statistical significance due to limited within-region variation of our treatment across only three survey waves.

Table 5: Effect of Natural Disasters on Green Innovation and Climate Affectedness

	Green Innovation Combined (1)	Within-firm Process Innovation (2)	Green Products (3)	Climate Affectedness (4)
Cumulative Count	2.16***	2.08***	1.63***	5.58***
	(0.283)	(0.287)	(0.237)	(0.691)
Firm Size F.E. (employment)	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	No (Single Wave)
Industry F.E. (2-digit NACE)	Yes	Yes	Yes	Yes
Observations	15,395	15,426	15,226	4,873
R^2	0.629	0.591	0.451	0.582
Adj. R^2	0.627	0.589	0.448	0.576

Note: This table reports the effect of the cumulative number of past natural disasters on several survey outcomes. Column (2) reports results for within-firm process innovation, columns (3) for a firm introducing new green products, and column (1) for both of these combined. Column (4) reports the effect on firms' self-reported climate affectedness. All models include firm size (based on employment dummies), revenue controls, year fixed effects, and 2-digit NACE industry fixed effects. Standard errors are clustered at the regional (Kreis) level. Significance levels: *p<0.1; **p<0.05; ***p<0.01.

Additionally, we examine whether firms exposed to natural disasters report experiencing their effects. In the last wave of the survey firms were asked how important various climate-related impacts were between 2018 and 2020, we create a dummy variable equal to one if the item "Impact of extreme weather conditions" (e.g., transport disruptions, storm damage, flooding, drought) was rated as high, medium, or low importance. Firms in disaster-affected areas are significantly more likely to report experiencing climate-related impacts, providing a strong first stage for our analysis (see column (4) in Table 5).

5 Reasons to Innovate

In this section, we investigate the underlying reasons why inventors respond to natural disasters, by drawing on additional survey items in the CIS environmental innovation module.

[19] This corresponds to the 2.08% and 1.63% percentage points increase in Table 5.

Conditional on reporting the introduction of an innovation with environmental benefits, firms were asked to assess the importance of various potential drivers. These include existing environmental regulations, anticipated future regulations or taxes, voluntary standards or best practices within the industry, current or expected market demand, government funding or subsidies, and reputational concerns. The precise question text reads as:

> "During [the past two years], how important were the following factors in driving your enterprise's decision to introduce innovations with environmental benefits?"

Each factor generates a dummy equal to one if it was rated "low," "medium," or "high" importance, and zero if deemed "not relevant" (see Appendix C.2 for details).

The primary drivers of green innovations among the surveyed firms are existing environmental regulations, with 63.3% of firms identifying this factor as significant. Voluntary actions or standards for environmental best practices within their sector were noted as important by 57.9% of firms. Anticipated future regulations or taxes motivated 55.6% of the firms, while current or expected market demand for environmental innovations influenced 49.1%. Lastly, 40.7% of firms cited government grants and subsidies as a key motivating factor.

We then estimate the effect of natural disaster exposure on each of these drivers using

$$Y_{ilkt} = \beta\left(\sum_{s=0}^{\infty} d_{l,t-s}\right) + \gamma_1\,\mathbf{S}_{it} + \gamma_2\,R_{it} + \gamma_3\,\lambda_t + \gamma_4\,\lambda_k + \epsilon_{iltk}, \tag{8}$$

where Y_{ilkt} indicates whether firm i in region l in industry k at time t rated the factor as relevant; $\sum_{s=0}^{\infty} d_{l,t-s}$ is the count of natural disasters prior to questioning; $\mathbf{S}_{it}$ is a vector of firm-size dummies for medium and large firms, with small firms being the reference group; R_{it} is firm i's revenue in year t; λ_t and λ_k are year and two-digit NACE industry fixed effects; and ϵ_{iltk} is an idiosyncratic error term clustered at the NUTS-3 (Kreis) level. The firm-size dummies $\mathbf{S}_{it}$ are based on the number of employees. Specifically, we differentiate small firms with less than 50 employees, medium firms with 50-249 employees, and large firms employing more than 249 individuals. Our coefficient of interest β estimates the effect one additional past natural disaster has on a firm's probability of stating a factor as relevant for their green innovation decision. The comparison is between firms that have recently introduced a green innovation and have been affected by a natural disaster, and those firms that have introduced a green innovation but have not been affected by a natural disaster. Table 6 gives our results.

In column (1) of Table 6, a one-unit increase in the count of past natural disasters raises the probability of mentioning expected future regulation by 0.932 percentage points on a baseline mean of 63.33 percent, a highly significant effect at the 1 percent level. Column (2)

Table 6: Effect of Cumulative Disaster Count on Reasons to Innovate

	Dependent variable:					
	Expected Regulation	Expected Demand	Existing Regulation	Public Funding	Voluntary Standard	Reputation
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Count	0.932***	0.865***	0.748***	0.169	1.140***	0.391
	(0.266)	(0.263)	(0.263)	(0.269)	(0.218)	(0.313)
Firm Size F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E. (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Y	63.33	55.64	40.66	49.07	57.95	61.47
Observations	8,787	8,754	8,862	8,776	8,782	5,423
R^2	0.548	0.489	0.607	0.418	0.543	0.667
Adj. R^2	0.544	0.484	0.603	0.413	0.539	0.662

Note: This table reports the effect of disaster exposure on the drivers of innovation as measured in the survey. One additional past disaster increases the probability of a firm mentioning these factors by β percentage points (e.g. for column 1 by β=0.932 percentage points). Outcomes are: Expected Regulation = expected future environmental rules; Expected Demand = expected future market demand for green innovation; Existing Regulation = current environmental rules/charges; Public Funding = government grants/subsidies; Voluntary Standard = voluntarily joining a standard for green practices (e.g. environmental/organic label); Reputation = firm's reputation concerns. Standard errors clustered at the region (NUTS-3) level and are reported in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

shows a similarly strong response for expected demand: each additional disaster increases the likelihood of reporting anticipated market demand as a motivator by 0.865 percentage points, relative to a 55.64 percent mean. Firms also become 0.748 percentage points more likely to point to existing environmental regulations (mean 40.66 percent). By contrast, the effects on public funding and reputation concerns are small and statistically indistinguishable from zero. Voluntary standards show a sizable 1.140 percentage-point increase (57.95 percent mean). Taken together, these results suggest that natural disasters most strongly amplify firms' expectations about future regulation and market demand, with more modest or no effects on public funding and reputational motives.

We interpret the effects on expected regulation and expected demand as firms expecting consumers to increasingly value green alternatives in the future—not only through their purchasing decisions but also through political support for stricter environmental policies. In essence, experiencing a natural disaster changes higher-order beliefs (beliefs about the beliefs of others) about consumers' climate change beliefs and their valuation of green consumption and green policy. In turn, this expectation of stronger consumer environmental consciousness leads firms to foresee greater pecuniary returns to investing in green innovation. Prior research documents that natural disaster exposure shifts beliefs toward greater support for environmental policy. Dechezleprêtre et al. (2022) and Djourelova et al. (2024) show that disasters increase the salience of environmental issues. Owen et al. (2012) and Osberghaus and Fugger (2022) find that personal disaster experience heightens perceived climate risks and support for environmental regulation.

Our findings also point to firms increasing their awareness of existing environmental regulation. A potential reason is the increased salience of such policies. An increase in local climate change salience leads firms to pay closer attention to related topics, such as environmental regulation.

The positive effect on firms citing voluntary standards as primary reasons for innovation can be attributed to two different channels. First, firms might join voluntary standards due to the signaling value these standards have for consumers. Being able to label your products as e.g. "micro-plastic-free" or can attract consumers (Agatz et al. 2021, Duckworth et al. 2022). Second, firms may engage in green innovation due to intrinsic motivation. Intrinsic motivation refers to the idea that there is no reward for an activity other than the activity itself. This includes acting based on ethical convictions or long-term sustainability goals, even in the absence of financial rewards. In our setting, exposure to natural disasters may shift firms' internal priorities in this direction. We view reputational concerns as being potentially aligned with such non-monetary motivations.

In Section B.8 in the Online Appendix, we additionally include NUTS-2-level and region-level fixed effects.[20] Results remain robust when we include NUTS-2 level fixed effects. When including region-level fixed effects, our point estimates remain similar, but become statistically insignificant apart from for the effect on "Expected Regulation". When including region-level fixed effects we lose a lot of our underlying disaster variation, as we only have three survey waves.

Natural disaster exposure does not affect firms' self-reported take-up of public funding schemes. To further assess whether government research support could explain the observed increase in green innovation, we analyze administrative data on French public R&D funding (see Section B.8.1 in the Online Appendix). We find no significant changes in the number of grants or funding levels in disaster-affected regions, further underlining that the innovation response is not driven by targeted public subsidies.

Our proposed mechanism—complementing other potential channels—is that exposure to natural disasters increases the local salience of climate change. This increase in salience can have multiple effects on inventors and inventive firms. It shapes local inventors' expectations regarding environmental policy and the demand for green goods. These expectations are driven by inventors' higher-order beliefs about the climate change beliefs of consumers and voters. Increased salience further leads to an increase in attention to climate change and potentially affects inventors' and firms' intrinsic motivation.

[20] In Germany, the NUTS-2 level corresponds to current and former "Bezirke", which are administrative regions that are below the "Länder". The city states of Berlin, Hamburg, and Bremen, as well as the federal states of Brandenburg, Mecklenburg-Western Pomerania, Schleswig-Holstein, Saxony-Anhalt, Saarland, and Thuringia, do not have any NUTS-2 level subdivision and are thus themselves NUTS-2 level areas.

6 The Market for Green Goods

In this section, we introduce a model that captures how disaster-induced salience affects green innovation, both through inventors' intrinsic motivation and profit-driven responses to anticipated shifts in consumer demand. We formalize our behavioral mechanism and examine its interaction with market forces. To do so, we adapt and extend the framework proposed by Aghion et al. (2023), whose core insight is that green innovation responds to consumer demand for environmentally friendly products. A key feature of their model is that market structure matters: firms facing intense product market competition benefit more from "escaping" competition by developing green products that differentiate them from incumbents.

We add a behavioral channel through which inventors form expectations about future consumer demand in response to natural disasters. We introduce uncertainty about future demand and allow inventors to derive intrinsic utility from pursuing environmentally beneficial innovation. Both expectations and intrinsic motives vary across regions and are shaped by local natural disaster exposure. This extension is motivated by our empirical finding in Table 3, which shows limited evidence of geographic spillovers from neighboring disasters, suggesting that behavioral responses are highly localized.

6.1 Model

Inventors choose R&D investments aiming to maximize expected profits. Once innovations have realized, they produce with their respective technologies and compete for consumers. Revenues are distributed as wages to production and R&D workers, and net profits are redistributed to consumers, who also own firms as shareholders. There is a continuum of horizontally differentiated goods indexed by $j \in [0, 1]$. For each variety, two duopolists and a competitive fringe supply otherwise identical products that differ only in their emissions intensity embodied in production. Producing one unit of the good with environmental quality $q_{j,f}$ generates $x_{j,f} = 1/q_{j,f}$ units of carbon emissions. Labor is the sole input, supplied perfectly elastically at a wage normalized to one. The marginal labor requirement per unit of output equals a constant $c > 0$.

The representative consumer derives utility from variety consumption but also experiences private disutility from their carbon footprint. These preferences could arise, for instance, from social image concerns or a general sense of responsibility toward the environment. When purchasing $y_{j,f}$ units from each firm $f \in \mathcal{F}_j$ in sector j, the period-t utility is given by:

$$U_t = \int_0^1 \ln \bar{y}_{j,t}\, dj, \quad \text{with} \quad \bar{y}_{j,t} = \int_{f \in \mathcal{F}_j} y_{j,f,t}\, q_{j,f,t}^{\delta_{j,t}}\, df. \tag{9}$$

where $\bar{y}_{j,t}$ is the quality-adjusted consumption of good j, purchasable from various firms $f \in \mathcal{F}_j$. The value of a green product depends positively on the stringency of environmental regulation, as stricter policies raise the relative costs of non-green alternatives. The parameter δ_j captures how individuals value their own private consumption and express their political preferences regarding environmental policy. Empirical evidence suggests exposure to natural disasters shifts local preferences towards stronger environmental policies.

The parameter δ_j is potentially heterogeneous across goods. For example, consumers might weigh their carbon footprint differently when purchasing meat versus vegetarian alternatives than when buying toothpaste. Such heterogeneity arises from differences in consumer awareness, labeling practices, and the psychological salience of environmental impacts across goods categories (Agatz et al. 2021, Duckworth et al. 2022). Additionally, climate policy is often sectoral to protect national interests or to appease a certain group of voters, which in turn makes climate policy more stringent in some product markets than others.

Varieties j are imperfect substitutes. Within each variety, all demand will be allocated to the firm offering the highest quality-to-price ratio, q^δ/p. Logarithmic preferences imply that expenditure is uniform across all varieties. For a formal derivation of this result, refer to Section A.1 in the Online Appendix. We assume that consumer demand is non-local. Once a product is patented, it is marketed globally.[21] This assumption enhances model tractability and is also grounded in the legal interpretation of patent rights. The Paris Convention for the Protection of Industrial Property (1883), which has been adopted almost universally, stipulates that an inventor who patents a product in one country has a 12-month window during which they can apply for protection in other contracting states. These subsequent applications are granted the same priority date as the original filing. This provision facilitates easier entry into international markets without risking loss of intellectual property rights to third parties. Even if an inventor decides not to patent their invention in some countries, the same invention cannot be patented there by others and is instead regarded as publicly accessible information.

We assume a market structure in which each sector features a duopoly, composed of two competing innovators, alongside a competitive fringe. The fringe consists of firms that do not invest in innovation and continue producing the previous-generation good, which is one step behind the technological frontier. These goods are γ times more polluting than those of the

[21] Although this assumption is strong, we demonstrate that our main results remain valid when restricting the analysis to globally marketed patents. See Section 4.3 for results focusing exclusively on triadic patents, which are filed globally.

duopolists and thus less attractive to environmentally conscious consumers. The presence of the fringe disciplines the market by limiting the pricing power of the duopolists. If the duopolists were to charge a price exceeding the marginal cost of the fringe good—adjusted for its lower environmental quality—consumers would switch to the cheaper, albeit dirtier, alternative. As a result, the duopolists, who have a quality advantage, cannot extract monopoly rents beyond what the quality differential justifies.

The quality of a green good y_j evolves according to $q_j = \gamma^{k_j}$, where $\gamma > 1$ denotes the step size of a green innovation, and k_j is the cumulative number of past innovations in variety j. Intuitively, each successful innovation improves the environmental performance of a good by a factor of γ. Innovation arises from directed R&D effort. Inventors can choose to exert research effort $z_j \in [0, 1]$, incurring convex costs of $\kappa z_j^2/2$ units of labor.[22] With probability z_j, the investment succeeds, improving the quality of the good by a factor of γ in the next period. With probability $1 - z_j$, the attempt fails, and no technological progress is achieved. Upon a successful innovation, the inventor receives a patent that grants it a temporary edge over its rival. To capture the entire market, a successful inventor engages in limit pricing, setting the price just low enough to undercut her competition—specifically at $p_M = \gamma^{\delta} c$. This allows the innovator to behave as a de facto monopolist for one period. After that, the patent expires, the quality gap closes, and market competition resumes.

An important aspect of an inventor's decision to innovate is how much she expects consumers to value green products. Consumer valuation of green goods δ_j evolves over time, and there exists local uncertainty regarding the future valuation level. The global level of δ could, for instance, depend on the degree of global exposure to climate change. Inventors are local and form Bayesian expectations about consumers' valuation of green goods based on a global prior ρ (common across all locations) and local events D_l:

$$E_l[\delta_j] = \varphi\rho + (1 - \varphi)\phi D_l, \tag{10}$$

where ϕ denotes the size of the local shock. Inventors' expectations can fall whenever they are unaffected by natural disasters. We define the average expectation of consumer valuation for green goods across locations as:

$$\overline{E_l[\delta_j]} = \int_l E_l[\delta_j] f(l)\, dl = \varphi\rho + (1 - \varphi)\int_l \phi D_l f(l)\, dl = \varphi\rho + (1 - \varphi)\phi\overline{D_l}$$

where $f(l)$ denotes the probability density function over regions l, and $\overline{D_l}$ is the average level

[22] Convex innovation costs are a plausible assumption, as reducing the environmental impact of goods becomes increasingly difficult. For example, designing a plane that consumes slightly less fuel is much easier than creating one that emits no CO_2 at all.

of disaster exposure. We denote this benchmark as $\overline{E}[\cdot]$, which reflects the average belief held across all locations. Inventors' expectations may deviate from this average depending on their local exposure. In regions recently affected by natural disasters, inventors may hold higher expectations about the future valuation of green goods ($E_l[\delta_j] > \hat{E}[\delta_j]$), while inventors in unaffected areas may hold lower expectations ($E_l[\delta_j] < \hat{E}[\delta_j]$). For our welfare analysis, we assume that the social planner takes this average expectation as given when choosing the optimal innovation rate. We define the planner belief as $\hat{E}[\delta_j] \equiv \overline{E_l[\delta_j]}$.

Inventors derive utility both from the profits of their innovation activity and from the intrinsic satisfaction of pursuing research. For tractability, we assume the factors are linearly separable in the utility function.

$$U_l^I(z_{lj}) = \alpha \Pi(z_{lj}) + \mu_l z_{lj}$$

where the parameter α captures the weight on monetary rewards, while μ_l reflects the inventor's intrinsic motivation—specifically, the non-pecuniary utility derived from engaging in green innovation. Intrinsic motivation may stem from ethical concerns, a sense of moral responsibility, or personal interest in mitigating climate change. Importantly, μ_l may vary across regions and can be shaped by local experiences, such as exposure to natural disasters. Inventors with a high μ_l are thus more likely to engage in green innovation for its own sake, independent of financial incentives. At the time of investing in research, inventors form expectations over output and profitability, conditional on successful innovation:

$$E_l[y_{Mj}] = \frac{1}{E[p_{Mj}]} = \frac{1}{\gamma^{E_l[\delta_j]}c}, \quad \text{and} \quad E_l[\pi_{Mj}] = 1 - \frac{1}{\gamma^{E_l[\delta_j]}}, \tag{11}$$

Local expectations $\gamma^{E_l[\delta_j]}$ shape the profit component of utility and are critical for investment decisions. A formal derivation of expected demand and profits is provided in Section A.1 of the Online Appendix.[23]

In markets where no innovation takes place, the duopolists engage in price competition. If they can collude perfectly, they charge the monopoly price and share profits equally. They are constrained by the competitive fringe. In contrast, under full competition, firms bid prices down to marginal cost. Following Aghion et al. (2005), we model the intensity of competition as $\Delta_j \in [1/2, 1]$, where $\Delta_j = 1$ corresponds to Bertrand competition and $\Delta_j = 1/2$ reflects full collusion. Duopoly profits thus depend on the degree of competition

[23] For comparison, the social planner holds expectations based on the average valuation across locations, represented by $\gamma^{\overline{E[\delta_j]}}$. These average beliefs determine the socially optimal direction and scale of innovation across regions. See Section A.3 in the Online Appendix for the welfare analysis.

in sector j, and are a fraction of expected monopoly profits:

$$E_l\left[\pi_{Dj}(\Delta_j)\right] = (1-\Delta_j)\, E_l\left[\pi_{Mj}\right]. \tag{12}$$

Given this structure, the locally expected price under imperfect competition is:

$$E_l\left[p_j(\Delta_j)\right] = \frac{c}{1-2(1-\Delta_j)E_l[\pi_{Mj}]} = \frac{c}{1-2(1-\Delta_j)\left(1-\gamma^{-E_l[\delta_j]}\right)} \in \left[c, E_l[p_{Mj}]\right], \tag{13}$$

and the corresponding expected output is:

$$E_l\left[y_j(\Delta_j)\right] = \frac{1}{E_l[p_j(\Delta_j)]} = \frac{1}{c}\left[1-2(1-\Delta_j)\left(1-\gamma^{-E_l[\delta_j]}\right)\right] \in \left[E_l[y_{Mj}], \frac{1}{c}\right]. \tag{14}$$

A local inventor in region l and sector j with an R&D opportunity maximizes

$$\max_{z_{lj}\in[0,1]} U^I(z_{lj}, \Delta_j, E_l(\delta_j), \mu_l) = \alpha\left(z_{lj}E_l\left[\pi_{Mj}\right] + (1-z_{lj})E_l\left[\pi_{Dj}(\Delta_j)\right] - \frac{\kappa}{2}z_{lj}^2\right) + \mu_l\, z_{lj}.$$

where successful innovation yields monopoly profits, and failure yields the duopoly profits dependent on the level of competition. The stronger the competition is, the larger the benefit of escaping competition by innovating becomes. Competition acts as a wedge between the profits of a successful inventor and the profits that inventors can reap in the status quo. The first-order condition of a local inventor with respect to the research rate is:

$$z_{lj} = \min\left\{\frac{E_l\left[\pi_{Mj}\right] - E_l\left[\pi_{Dj}(\Delta_j)\right]}{\kappa} + \frac{\mu_l}{\alpha\kappa}, 1\right\}. \tag{15}$$

Using (15) with (11) and (12), we get:

$$z_{lj}(\Delta_j, E_l(\delta_j), \mu_l) = \underbrace{\frac{\Delta_j\, E_l\left[\pi_{Mj}\right]}{\kappa}}_{\text{Monetary Incentives}} + \underbrace{\frac{\mu_l}{\alpha\kappa}}_{\text{Intrinsic Motivation}} = \frac{\Delta_j}{\kappa}\left(1-\frac{1}{\gamma^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha\kappa} \tag{16}$$

The optimal research rate consists of two additive components: the first reflects the monetary incentives to innovate, while the second captures the inventor's intrinsic motivation. The monetary incentive term increases with the intensity of competition Δ_j and with local beliefs about the profitability of green goods, captured by $E_l[\delta_j]$. Intuitively, when competition is intense (i.e., Δ_j is high), duopoly profits are low, making the gains from obtaining monopoly status through successful innovation more attractive. Similarly, higher expected consumer valuation for green goods leads to higher expected monopoly profits, further incentivizing R&D. Formally, innovation effort is increasing in both arguments: $\frac{\partial z_{lj}}{\partial \Delta_j} > 0$, $\frac{\partial z_{lj}}{\partial E_l[\delta_j]} > 0$. Moreover, these forces are complements, as shown by the positive cross-derivative: $\frac{\partial^2 z_{lj}}{\partial \Delta_j \partial E[\delta_j]} > 0$. Competition and demand expectations thus reinforce each other. In monopolistic markets, inventors already earn high rents from non-green products and respond little to shifts in consumer preferences. In contrast, under competitive pressure, inventors can escape price competition by innovating. When environmental quality matters to consumers, green innovation becomes a path to monopoly. Expected profits rise with both stronger demand expectations and higher competition.

The second term in Equation (16) reflects intrinsic motivation, scaled by the inventor-specific parameter μ_l. Importantly, this component is unaffected by market competition, as: $\frac{\partial^2 z_{lj}}{\partial \Delta_j \, \partial \mu_l} = 0$. This implies that inventors motivated purely by intrinsic factors—such as environmental concern or personal satisfaction—invest in green innovation regardless of the competitive landscape. Competition only plays a role for those inventors who value monetary rewards. Figure 7 visualizes these comparative statics.[24]

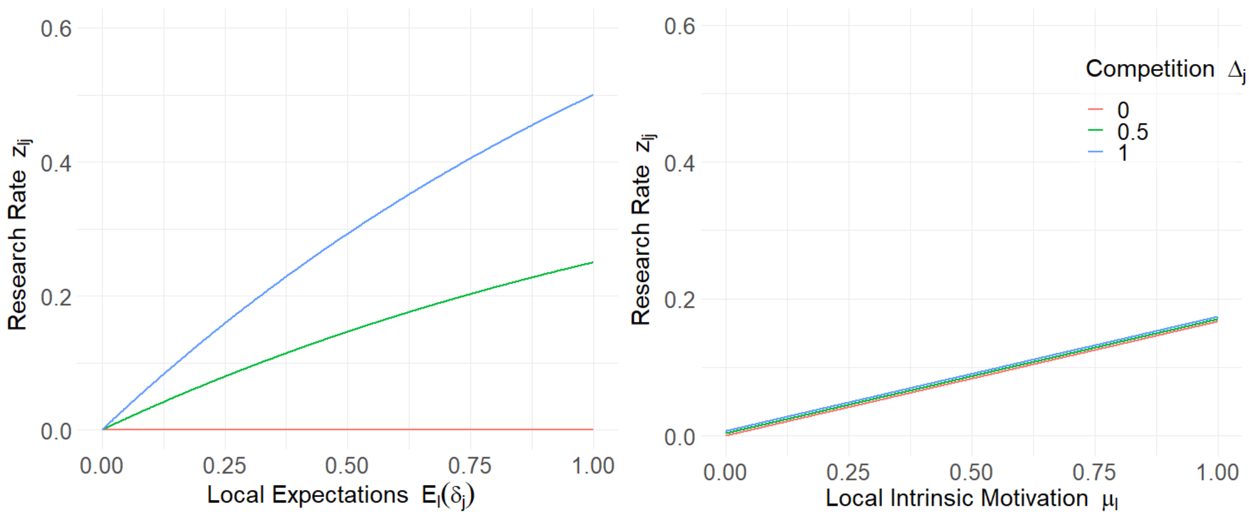


Figure 7: Innovation Responses dependent on Competition Δ_j

Note: The figure on the left plots inventors' innovation response dependent on their expectations $E_l(\delta_l)$ and the level of competition when intrinsic motivation plays no role ($\alpha \to \infty$). The figure on the right plots innovation responses only dependent on inventors' intrinsic motivation μ_l, i.e. for $\delta = 0$.

Hypothesis 1: Inventors facing fiercer competition (large Δ_j) increase their research output more whenever their profitability expectations increase due to exposure to a natural disaster.

In line with these comparative statics, we formulate the above empirically testable hypothesis. We can test Hypothesis 1 explicitly by comparing the response of inventors facing

[24]The figure is illustrative and highlights qualitative mechanisms. Quantitative implications depend on the specific calibration. For details, see Section A.4 in the Online Appendix.

high levels of competition with those facing low levels of competition. We confirm this empirically in Table 7 in Section 6.2.1, which provides compelling evidence that shifts in higher-order beliefs significantly influence inventors' innovation decisions. Intuitively, because competition only affects pecuniary incentives, differences in competition levels should impact only those inventors driven by monetary rewards. Purely intrinsically motivated inventors would respond to exposure irrespective of the level of competition (see the right-hand panel of Figure 7).

Generally, the overall (private) innovation rate in the economy is the average across all sectors j and locations l, which is equivalent to the fraction of sectors where innovation is successful

$$\underline{z} \equiv \int_j \int_l z_{lj}(\Delta_j, E_l(\delta_j), \mu_l) f(l) dl f(j) dj.$$

Let

$$\overline{z} \equiv \int_j z_j(\Delta_j, \overline{E(\delta_j)}, \overline{\mu}) f(j) dj$$

denote the research rate that would be achieved if all local inventors had the same (average across regions l) expectation on future environmental profitability $E_l(\delta_j) = \overline{E(\delta_j)}\ \forall l$ and intrinsic motivation $\mu_l = \overline{\mu}\ \forall l$. We can then compare $\overline{z}$ with the aggregate private research rate $\underline{z}$).

Assumption 1: Assume that the $E_l(\delta_j)$ are not degenerate, i.e., there exists some j such that

$$\exists\, l \neq l' \quad \text{with} \quad E_l(\delta_j) \neq E_{l'}(\delta_j).$$

Assumption 1 simply states that not all regions have identical expectations regarding future environmental demand. At least one region must differ in expectations, reflecting realistic variation in the exposure to natural disasters.

Proposition 1: Under Assumption 1, we get that:

$$\begin{aligned} \overline{z} &= \int_j \left(\frac{\Delta_j}{\kappa} \left(1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}} \right) + \frac{\overline{\mu}}{\alpha\kappa} \right) f(j) dj > \\ \underline{z} &= \int_j \int_l z_{lj}(\Delta_j, E_l[\delta_j], \mu_l) f(l) dl f(j) dj = \int_j \int_l \left(\frac{\Delta_j}{\kappa} \left(1 - \frac{1}{\gamma^{E_l[\delta_j]}} \right) + \frac{\mu_l}{\alpha\kappa} \right) f(l) dl f(j) dj \end{aligned} \tag{17}$$

The research rate achieved under average expectations is larger than the research rate achieved when expectations are heterogenous across regions. See Section A.2 in the Online Appendix for our proof of Proposition 1. Proposition 1 demonstrates that heterogeneous regional expectations generate inefficiencies in innovation. Specifically, due to the convexity of innovation costs, having uniform (average) expectations across regions would achieve either higher total innovation for the same cost, or the same innovation level at a lower cost, compared to a scenario where regions differ in their expectations.

Given the inefficiencies arising from heterogeneous expectations illustrated in Proposition 1, we investigate the implications of these inefficiencies for welfare. In Section A.3 in the Online Appendix, we show that the socially optimal rate of innovation is strictly higher than the privately chosen rate. Private innovation decisions systematically underreact to climate risks due to localized belief formation, imperfect competition, and a failure to fully internalize environmental externalities. Proposition 2 in the Appendix formalizes this result and quantifies these welfare inefficiencies. This underscores a clear rationale for policy interventions, such as enhancing climate awareness or subsidizing clean innovation in less-affected regions.

6.1.1 Building on the Shoulders of Giants & Market Size

We futher extend the model to incorporate market size effects, drawing on the literature on directed technical change, which emphasizes that the profitability of innovation increases with market size—a feature often referred to as "building on the shoulders of giants" (Acemoglu 2002; Acemoglu 2007; see also Acemoglu et al. 2012 for an application to green technologies). To do so, we explicitly model the cost of research as depending on the size of the market for green goods $K(\eta_j)$ with $\frac{\partial K}{\eta_j} < 0$. We then get that for any level of research effort $z_j \leq 1$, investing $K(\eta_j)z_j^2/2$ units of labor yields, with probability z_j, a green innovation. See section A.5 in the Online Appendix for an alternative modeling assumption, where the step size of innovation γ, as opposed to the cost, depends on market size. Results are qualitatively the same.

Similar to equation (16), we have that the optimal private research rate is chosen according to:

$$z_{lj}(\Delta_j, E_l(\delta_j), \mu_l, \eta_j) = \frac{\Delta_j E_l\left[\pi_{Mj}\right]}{K(\eta_j)} + \frac{\mu_l}{\alpha K(\eta_j)} = \frac{\Delta_j}{K(\eta_j)}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha K(\eta_j)}.$$

The optimal private research rate increases in the size of the market $\frac{\partial z_{lj}}{\partial \eta_j} > 0$. Additionally, inventor expectations about the profitability of a green good $E_l(\delta_j)$ and the market size of the green good η_j are complements: $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial E_l(\delta_j)} > 0$. Intuitively, inventors in large markets face lower innovation costs and respond more readily to increased expectations about green profitability and increased intrinsic motivation. We plot this comparative static in Section A.4 in the Online Appendix. This allows us to formulate an additional hypothesis:

Hypothesis 2: Innovation responses to natural disasters increase with the size of the green good market $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial E_l[\delta_j]} > 0$ and $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial \mu_l} > 0$. Put differently, the increase in innovation following exposure to natural disasters is larger in markets where the green technology market is bigger.

The main takeaways of our model are as follows: First, inventors facing stronger competition increase their research effort more in response to higher profitability expectations after natural disaster exposure. Since competition only affects pecuniary incentives and not intrinsic motivation, evidence supporting Hypothesis 1 would show that shifts in higher-order beliefs about future profits play a key role in driving innovation decisions. Second, heterogenous salience of climate change leads to higher aggregate costs for the same research output than homogenous salience of climate change would. This is due to research costs being convex. Third, a larger green good market induces stronger responses to changes in inventors intrinsic utility and expectations about consumers' valuation of green goods. Fourth, the overall private research rate in the economy is lower than the socially optimal research rate.

6.2 Empirical Results on Model Hypothesis

In this section, we test how market conditions and changes in inventors' expectations interact. Our findings reveal that first, a well-functioning market is essential to ensure that inventors respond to changes in the salience of climate change. Second, disaster induced changes in inventors monetary expectations matter for their innovation.

6.2.1 Competition

We first empirically test Hypothesis 1 of the model: inventors in more competitive industries should exhibit stronger green innovation responses to natural disaster exposure than those in less competitive industries. To briefly summarize the intuition behind this hypothesis: a monopolist does not have incentives to pursue green innovation, as green product differentiation does not increase her profits above the monopoly profits she already enjoys. An inventor in a competitive environment, on the other hand, stands to gain substantial monetary gains from differentiating their product.

To empirically test this hypothesis, we measure competition using industry-level profit margins from CompNet (2022), following Aghion et al. (2023). Higher profit margins reflect lower competition. A key advantage of this measure is that it captures international competition, unlike the Herfindahl–Hirschman index, which is country-specific. The CompNet database consolidates administrative firm-level data across European countries and reports aggregated indicators at various levels of industry and geography. For France and Germany, the data are available from 2003 and 2001, respectively. Both CompNet and PATSTAT use the European Classification of Economic Activities (NACE Rev. 2), allowing us to link patent filings to industry-level competition at the 2-digit level—the most granular available in CompNet. For patents associated with multiple industries, we use industry weights to compute a composite measure. For each patent, we calculate the associated profit margin $M(i)$ of patent i as:

$$M_{it} = \sum_c \omega_{ic} \sum_k w_{ik} \times \frac{(margin_{kc,t} + margin_{kc,t-1})}{2}$$

where ω_{ic} represents the share of patent i's inventors living in country c, and w_{ik} denotes the weight with which the patent belongs to a specific industry k. Lastly, $\frac{margin_{kc,t}+margin_{kc,t-1}}{2}$ is the average profit margin of industry k in country c during the year of filing and the prior year. The profit margin M_{it} of a patent i is thus the weighted average of the profit margins faced by its inventors at the time of invention and the year prior. For example, if a patent related to the automotive industry was filed in 2004 by one French and one German inventor, the associated profit margin would be the mean of the profit margins for both the German and French automotive industries in 2003 and 2004. In Online Appendix section B.10, we show our results for a 1-year and 3-year window of the profit margin. Results are similar.

Instead of splitting the sample based on the overall median level of competition across all patents, we conduct the split within industries. This avoids comparing structurally distinct sectors—such as the highly competitive LED industry and the less competitive airline industry—that may differ for reasons unrelated to competition intensity. Instead, we compare patents within a given industry during periods of relatively high and low competition. We define the "high-competition" group as patents with above-median competition within their industry, and the "low-competition" group as those below the within-industry median.

To implement this, we calculate a patent-specific benchmark competition level (BMC_i), based on the median competition level of each 2-digit NACE industry across all years. For each patent i, we compute:

$$BMC_i = \sum_c \omega_{ic} \sum_k w_{ik} \times \text{median(margin)}_{kc}$$

where $\text{median(margin)}_{kc}$ denotes the median competition level in industry k and country c, computed over the entire sample period. The weights ω_{ic} and w_{ik} reflect the country and industry affiliations of patent i, respectively. If a patent's observed competition level M_{it} exceeds its benchmark BMC_i, it is classified into the high-competition group; otherwise, it is assigned to the low-competition group. Since this procedure leads to different sample averages across groups, we normalize the outcome variable by the sample mean within each group to ensure comparability of results.

After splitting, we aggregate patents at the regional level separately for the high- and low-competition samples, resulting in two distinct region-by-year panels. For each sample, we estimate a difference-in-differences regression that compares changes in patenting activity before and after natural disasters across affected and unaffected regions. This allows us to separately identify the effect of natural disaster exposure on patenting for inventors in highly competitive and less competitive markets. By comparing the estimated disaster effects across the two groups, we can assess whether stronger pecuniary incentives (i.e., greater competition) amplify inventors' responses to disaster exposure. Columns (1) and (2) in Table 7 show our results.

Table 7: Competition and Green Product Split

	Dependent variable: $P(Y02_{lt})$			
	Competition Cutoff		Greenness Cutoff	
	High-Competition	Low-Competition	Above Median	Below Median
	(1)	(2)	(3)	(4)
Cumulative Count	0.104***	0.007	0.088***	0.063***
	(0.022)	(0.033)	(0.011)	(0.009)
Country-Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes
Wald-test p-value	0.0365**		0.0307**	
Sample Mean	1.9854	1.284	1.335	1.3248
Observations	8,283	8,283	14,307	14,307
R^2	0.653	0.535	0.625	0.788
Adj. R^2	0.617	0.486	0.603	0.776

Note: This table reports the results for our tests of the model's comparative statics. Columns (1)-(2) split the sample based on competition, while columns (3)-(4) split based on the greenness of the industry's products. Cumulative count is the count of past natural disasters. The Wald-tests examine if the coefficient for cumulative disaster count significantly differs between splits. We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})^2}{\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})}$, where: $\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}}) = \text{Var}(\hat{\beta}_{\text{eq1}}) + \text{Var}(\hat{\beta}_{\text{eq2}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq1}}, \hat{\beta}_{\text{eq2}})$. We can reject the Null hypothesis $H_0 : \beta_h = \beta_l$ against the alternative ($H_1 : \beta_h > \beta_l$) with the reported p values. Competition is measured as the average across filing year and the previous year. Greenness is calculated as average green product share across filing year and the previous year. Standard errors are clustered at the region level and reported in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Inventors respond significantly more strongly to natural disaster exposure when operating in highly competitive environments. This finding provides strong support for our hypothesis and is consistent with the predictions of our theoretical model. The difference in response between high- and low-competition settings is both economically and statistically significant; we reject the null of coefficient equality with a p-value of 0.0365** (see Table 7 and the accompanying Wald test).

The lack of a response in low-competition environments suggests that pecuniary incentives play a central role in driving the observed innovation effects. If responses were primarily driven by intrinsic motivation, we would expect to see effects even in less competitive settings. Monetary incentives matter for how innovation responds to climate change. Our results highlight the importance of functioning competitive markets in enabling innovation to respond to climate-related shocks.

6.2.2 Green Good Demand

We next test Hypothesis 2, which predicts that a larger green goods market amplifies inventors' response to natural disaster exposure, as market size reduces the cost of innovation.

To empirically capture green market size, we use data from PRODCOM, a Eurostat database that reports annual production values for over 4,000 manufactured goods in Europe. Each product is classified using an 8-digit PRODCOM code, with the first four digits aligned to NACE industry codes. We identify green goods using the taxonomy developed by Bontadini and Vona (2023), which refines earlier lists compiled by the WTO and OECD. We update their list to reflect changes in PRODCOM codes over time (see Appendix C.3) and restrict to data from 1995 to 2014 for France and Germany. For each industry-year cell, we compute the share of green goods by production value:

$$\text{Green Share}jt = \frac{\sum gy_{jt,g}}{\sum_g y_{jt,g} + \sum_{ng} y_{jt,ng}} \tag{18}$$

where $y_{jt,g}$ and $y_{jt,ng}$ denote the production values of green and non-green products, respectively, in industry j and year t. We assign each patent a corresponding green market share based on the industries to which it is linked. Since patents may span multiple industries, we compute a weighted average using industry weights ω_{ij}:

$$\text{Green Share Patent}i = \sum_j \omega ij \cdot \frac{\text{Green Share}jt + \text{Green Share}jt - 1}{2} \tag{19}$$

where t is the filing year. This characterizes each patent by the green intensity of its market environment in the year of filing and the prior year. Results are robust to using a 1-year or 3-year window instead (Appendix B.11). We then split the sample of green patents by whether they fall above or below the median green market share and estimate regressions separately for each group. Results are presented in columns (3) and (4) of Table 7.

We find that market size plays a significant role in shaping inventors' responses. Inventors in industries with larger green product markets respond more strongly to disaster exposure than those in less developed green markets. The difference is statistically significant (Wald test p-value = 0.0307). These results align with the predictions of the directed technical change framework: larger green markets amplify the expected returns to green innovation following disaster exposure. Since market size and inventor expectations are complementary, the effects are strongest where both are aligned.

Together, these findings underscore the central role of market incentives in shaping innovation responses to climate change, and the importance of well-functioning, competitive markets in ensuring that inventors act on heightened climate salience.

7 Conclusion

This paper demonstrates that personal experiences affect inventors' research choices, bridging the literatures on experience effects and the drivers of innovation. We show that experiencing natural disasters significantly increases the invention of green technologies aimed at mitigation. This effect is highly localized and depends on direct personal experience. The effect is stronger in competitive markets and sectors with preexisting green demand.

Our empirical findings and theoretical framework point to a central mechanism: natural disaster exposure alters inventors' higher-order beliefs about consumer beliefs, increasing expectations of future green demand and regulatory tightening. This raises the perceived profitability of green R&D. The effect is strongest in competitive markets, where firms are more responsive to shifts in expected demand. While intrinsic motivation may also matter, our results highlight the central role of profit expectations in shaping innovation responses. These findings extend the experience-effects literature to the production side of the economy. Prior work has shown how personal experiences shape household expectations; we show they also influence high-stakes investment decisions with global implications.

We document an endogenous channel through which climate shocks affect the direction of technological change. Climate change is among the defining challenges of the twenty-first century. Its projected impacts—including more frequent floods (Hirabayashi et al. 2013; Roudier et al. 2016), deteriorating environmental conditions (Intergovernmental Panel on Climate Change (IPCC) 2023), and sea-level rise between 30 and 240 centimeters (Jackson 2022)—are both severe and global in scope. The economic literature highlights technological innovation, particularly in mitigation, as essential to addressing these risks (Acemoglu et al. 2012; Acemoglu et al. 2016). Yet, how innovation itself responds to climate change remains insufficiently understood. Our results suggest that forward-looking technological change may be more adaptive to rising climate risk than is typically assumed in integrated assessment models.

Beyond its theoretical contributions, our study has practical implications for policy. A well-functioning market and consumers' belief in anthropogenic climate change are crucial to ensuring that inventors act on increases in climate change salience. The local nature of responses, however, leads to inefficiencies. This indicates that coordinated policies could enhance the global benefits of climate-related technological progress. Our findings emphasize the role of private-sector incentives in shaping climate change-mitigating innovation.

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A Online Appendix - Theory

This appendix formalizes the consumer demand structure, characterizes equilibrium outcomes for monopoly producers, and offers our proofs. It also includes welfare analysis and explores alternative ways of modeling market size effects on innovation.

A.1 Demand & Market-Clearing

We consider a consumer with utility

$$U = \int_0^1 \ln \bar{y}_j \, dj, \quad \text{where} \quad \bar{y}_j = \int_{\mathcal{F}_j} y_{j,f} \, (q_{j,f})^{\delta_j} \, df,$$

subject to the overall budget constraint

$$\int_0^1 \int_{\mathcal{F}_j} p_{j,f} \, y_{j,f} \, df \, dj = M.$$

Intra-Good Optimization

For each good j, assume the consumer allocates an expenditure m_j (with $\int_0^1 m_j \, dj = M$) across varieties $f \in \mathcal{F}_j$ by solving

$$\max_{\{y_{j,f}\}} \ln \left(\int_{\mathcal{F}_j} y_{j,f} \, (q_{j,f})^{\delta_j} \, df \right)$$

subject to

$$\int_{\mathcal{F}_j} p_{j,f} \, y_{j,f} \, df = m_j.$$

Defining

$$\bar{y}_j = \int_{\mathcal{F}_j} y_{j,f} \, (q_{j,f})^{\delta_j} \, df,$$

the Lagrangian for this subproblem is

$$\mathcal{L}_j = \ln(\bar{y}_j) - \lambda_j \left(\int_{\mathcal{F}_j} p_{j,f} \, y_{j,f} \, df - m_j \right).$$

Taking the first-order condition with respect to $y_{j,f}$ gives

$$\frac{(q_{j,f})^{\delta_j}}{\bar{y}_j} - \lambda_j \, p_{j,f} = 0 \quad \Longrightarrow \quad \frac{(q_{j,f})^{\delta_j}}{p_{j,f}} = \lambda_j \, \bar{y}_j \quad \forall f \text{ with } y_{j,f} > 0.$$

Thus, only those varieties that maximize the ratio

$$\frac{(q_{j,f})^{\delta_j}}{p_{j,f}}$$

can receive positive demand. Define

$$f^*(j) = \arg\max_{f \in \mathcal{F}_j} \frac{(q_{j,f})^{\delta_j}}{p_{j,f}}.$$

Then all expenditure in good j is allocated to variety $f^*(j)$. The budget within good j therefore satisfies

$$p_{j,f^*(j)}\, y_{j,f^*(j)} = m_j,$$

so that

$$y_{j,f^*(j)} = \frac{m_j}{p_{j,f^*(j)}}$$

and

$$\bar{y}_j = \frac{m_j}{p_{j,f^*(j)}} (q_{j,f^*(j)})^{\delta_j}.$$

Allocation Across Goods

Substituting the expression for $\bar{y}_j$ into the overall utility yields

$$U = \int_0^1 \ln \left[\frac{m_j}{p_{j,f^*(j)}} (q_{j,f^*(j)})^{\delta_j} \right] dj = \int_0^1 \Big\{ \ln m_j - \ln p_{j,f^*(j)} + \delta_j \, \ln(q_{j,f^*(j)}) \Big\} dj.$$

The allocation $\{m_j\}$ is chosen subject to

$$\int_0^1 m_j \, dj = M.$$

Form the Lagrangian for the allocation across goods:

$$\mathcal{L} = \int_0^1 \ln m_j \, dj - \int_0^1 \ln p_{j,f^*(j)} \, dj + \int_0^1 \delta_j \, \ln(q_{j,f^*(j)}) \, dj + \theta \left(M - \int_0^1 m_j \, dj \right).$$

Taking the derivative with respect to m_j for each j gives

$$\frac{1}{m_j} - \theta = 0 \quad \Longrightarrow \quad m_j = \frac{1}{\theta}, \quad \forall\, j.$$

Then $\int_0^1 m_j \, dj = M$ implies

$$\frac{1}{\theta} = M \quad \Longrightarrow \quad \theta = \frac{1}{M}.$$

Hence, the optimal allocation is

$$m_j = M \quad \text{for all } j \in [0,1],$$

so that each good j receives an equal share of the total budget.

Characterization of Expected Monopoly Outcomes

Due to the structure of consumer demand, a successful inventor who upgrades quality by a factor γ faces the unsuccessful producer whose quality remains one "step" behind, $q_{\text{comp}} = q_M/\gamma$, and who sells at marginal cost c. Indifference between the innovator's variety and that of her competition requires

$$p_{Mj} \, (q_M)^{\delta_j} \;=\; p_{\text{comp}} \left(q_M/\gamma\right)^{\delta_j} \;\Longrightarrow\; p_{Mj} \;=\; \gamma^{\delta_j} \, c.$$

With total expenditure on good j normalized to one, this implies

$$y_{Mj} \;=\; \frac{1}{p_{Mj}} \;=\; \frac{1}{\gamma^{\delta_j} \, c}, \qquad \pi_{Mj} \;=\; 1 - \frac{c}{p_{Mj}} \;=\; 1 - \gamma^{-\delta_j}.$$

Taking local expectations $E_l[\cdot]$ over δ_j immediately yields

$$E_l[y_{Mj}] = \frac{1}{E_l[p_{Mj}]} = \frac{1}{\gamma^{E_l[\delta_j]} \, c}, \qquad E_l[\pi_{Mj}] = 1 - \frac{1}{\gamma^{E_l[\delta_j]}},$$

as in (11). Thus, prospective inventors anticipate these output and profits whenever their R&D succeeds.

A.2 Proof of Proposition 1

In this Section we proof Proposition 1 of Section 6. We know that $\gamma > 1$ and that for each j we have: $E[\delta_j] \geq 0$. Let

$$\Phi\left(E[\delta_j]\right) \equiv 1 - \frac{1}{\gamma^{E[\delta_j]}}.$$

A straightforward calculation shows that

$$\Phi'(x) = \gamma^{-x} \ln \gamma \quad \text{and} \quad \Phi''(x) = -\gamma^{-x} (\ln \gamma)^2.$$

Since $\gamma^{-x} > 0$ for all $x \geq 0$ and $\ln \gamma > 0$, it follows that $\Phi''(x) < 0 \quad$ for all $x \geq 0$. Thus, Φ is strictly concave on $[0, \infty)$. Let the average environmental expectation across regions be: $\overline{E(\delta_j)} = \int_l E_l[\delta_j]\, f(l)\, dl$. Then, by Jensen's inequality for the strictly concave function Φ, we have

$$\Phi\Big(\overline{E_l(\delta_j)}\Big) > \int_l \Phi\Big(E_l[\delta_j]\Big) f(l)\, dl, \tag{20}$$

provided that the $E_l[\delta_j]$ are not degenerate. Explicitly, this is

$$1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}} > \int_l \left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) f(l)\, dl.$$

Multiplying both sides of (20) by the positive constant Δ_j/κ yields

$$\frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}}\right) > \frac{\Delta_j}{\kappa}\int_l \left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) f(l)\, dl.$$

Now, suppose the intrinsic motivation is heterogeneous (i.e., it may vary with l). The average of intrinsic motivation μ_l is defined as: $\overline{\mu} = \int_l \mu_l\, f(l)\, dl$. Since the intrinsic motivation term enters linearly, we have

$$\frac{\overline{\mu}}{\alpha\kappa} = \int_l \frac{\mu_l}{\alpha\kappa}\, f(l)\, dl.$$

Therefore, adding these linear terms to both sides we obtain

$$\frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}}\right) + \frac{\overline{\mu}}{\alpha\kappa} > \int_l \left[\frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha\kappa}\right] f(l)\, dl \quad \forall j. \tag{21}$$

Inequality (21) completes the proof. Notice that the nonlinearity (and hence the strict inequality) originates solely from the concave function Φ; the linear intrinsic motivation term averages exactly.

A.3 Welfare

We now turn our eye to societal welfare. Societal welfare depends on quality-adjusted consumption (9) for all consumers and the externality dependent on emissions. Consumers are homogeneous and of mass 1. The welfare problem then boils down to maximizing the utility of a representative consumer. The level of tomorrow's emissions depends on current research input. With consumption expenditure normalized to 1, aggregate emissions are then:

$$X = \int_j (1 - z_j) y(\Delta_j) + z_{lj} y_{M_j}/\gamma dj \tag{22}$$

Total emissions are the sum of emissions over all sectors where innovation was unsuccessful, plus all emissions in sectors where innovation was successful with production being γ times less polluting. Societal welfare is negatively affected by these emissions with a factor $\psi > 0$.

The social planner has expectations:

$$\hat{E}[y_{Mj}] = \frac{1}{E[p_{Mj}]} = \frac{1}{\gamma^{\overline{E[\delta_j]}}C}, \quad \hat{E}[\pi_{Mj}] = 1 - \frac{1}{\gamma^{\overline{E[\delta_j]}}}. \tag{23}$$

where $\gamma^{\overline{E[\delta_j]}}$ is the expectation about the average valuation of a quality improvement γ in good market j.

In our setting, the social planner can choose the research rate in every sector j, which then determines good quality. The social planner maximizes welfare by choosing societal research rate(s) z_j:

$$\begin{aligned}\max_{z_j} W = \int_j & (1-z_j)\ln \hat{E}[y(\Delta_j)] + z_j \ln\left(\gamma^{\overline{E[\delta_j]}}\hat{E}[y_{M_j}]\right) \\ & -\psi\left[(1-z_j)\hat{E}[y(\Delta_j)] + z_j\hat{E}[y_{M_j}]/\gamma\right] \\ & . + \lambda\left[(1-z_j)(1-\Delta_j)\hat{E}[\pi_{M_j}] + z_j\hat{E}[\pi_{M_j}] - K(\eta_j)z_j^2/2 + \frac{\overline{\mu}}{\alpha\kappa}\right] dj\end{aligned} \tag{24}$$

The condition

$$(1-z_j)(1-\Delta_j)\hat{E}[\pi_{M_j}] + z_j\hat{E}[\pi_{M_j}] - \frac{K(\eta_j)z_j^2}{2} + \frac{\overline{\mu}}{\alpha\kappa} \geq 0$$

stipulates that inventors utility is positive and acts as a sort of resource constraint. λ then gives the degree to which inventor profits/utility can be traded off against research costs. Put differently, λ denotes the value the social planner attaches to innovators' profits/utility. When $\lambda \to \infty$, the social planner simply maximizes inventor profits/utility.

Proposition 2: Under assumption 1 we get that:

$$\begin{aligned} z_j^*(\Delta_j, \overline{E(\delta_j)}, \eta_j) &= \underbrace{\overline{z_j}(\Delta_j, \overline{E_l(\delta_j)}, \eta_j)}_{\text{average expectations}} \\ &+ \frac{1}{\lambda K(\eta_j)} \left[\underbrace{\ln \left[\frac{\gamma^{\overline{E[\delta_j}]} \hat{E}[y_{M_j}]}{\hat{E}[y(\Delta_j)]} \right]}_{\text{collusion loss}} + \underbrace{\psi \left[\hat{E}[y(\Delta_j)] - \hat{E}[y_{M_j}]/\gamma \right]}_{\text{emission reduction}} \right] \\ &> \underbrace{\underline{z_j}(\Delta_j, E_l[\delta_j], \eta_j)}_{\text{local expectations}} \end{aligned} \tag{25}$$

If at least one region is differentially affected, in every sector the optimal research rate chosen by the social planner is strictly larger than the average private research rate. Broken down by its components, the socially optimal research rate $z_j^*(\Delta_j, \overline{E(\delta_j)}, \eta_j)$ is the research rate achieved iff all inventors internalize the effects of climate change regardless of their personal exposure plus a term that corrects the inefficiency from imperfect competition and adds incentives to innovate in order to reduce emissions. See section A.3.1 in the appendix for our proof of proposition 2.

In addition to the loss in research rate due to local expectations $\overline{z_j} - \underline{z_j}$, the overall research rate is below the societal optimum due to collusion and inventors failing to internalize the emission benefit. The loss due to collusion and inventors failing to inernalize the emission reduction is scaled by the market size of a product j. We believe that a policymaker can likely observe more, if not all, natural disasters and form better expectations than local inventors can. Therefore, there is scope for policy to act by raising the salience of climate change in unaffected regions or, alternatively, incentivizing research in unaffected regions. Based on the optimal research rate of the social planner, increasing climate change salience unlikely "hurt," since the socially optimal research rate also corrects for imperfect competition and the emission externality.

Lastly, if one is willing to assume that the social planner has a better understanding of climate change dynamics, such as increased future disaster risk etc., the social planner could further improve on market outcomes by anticipating how these changes affect future environmental preferences. If, for instance, market participants systematically underestimate future disaster risks such that planner expectations $\hat{E}[\delta] > \overline{E[\delta]}$, then there is further scope for policy by correcting these optimistic (from the point of climate change) beliefs. We indeed believe that our results point toward the market underestimating the degree of climate change, as the innovation response is only ever following, and not anticipating, natural disaster exposure. However, it is less clear that an actual policymaker can fare significantly better than the market in this regard.

A.3.1 Proof of Proposition 2

In this section we proof Proposition 2 in Section A.3.

Let

$$\underline{z_j}(\Delta_j, E_l[\delta_j], \eta_j) \equiv \int_l \left(\frac{\Delta_j}{K(\eta_j)} \left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha\kappa} \right) f(l)dl$$

be defined as the average private research rate in sector j across all regions l. And let

$$\overline{z_j}(\Delta_j, \overline{E(\delta_j)}, \eta_j) \equiv \frac{\Delta_j}{K(\eta_j)} \left(1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}}\right) + \frac{\overline{\mu}}{\alpha\kappa}$$

be defined as the research rate achieved if all regions had average expectations. While proposition 1 (equation 17) does not have heterogeneous market size, it is straightforward to extend to this case, resulting in the following analogous condition $\forall j$:

$$\frac{\Delta_j}{K(\eta_j)} \left(1 - \frac{1}{\gamma^{\overline{E(\delta_j)}}}\right) + \frac{\overline{\mu}}{\alpha\kappa} > \int_l \left(\frac{\Delta_j}{K(\eta_j)} \left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha\kappa} \right) f(l)dl \tag{26}$$

Therefore, we have that $\overline{z_j}(\Delta_j, \overline{E(\delta_j)}, \eta_j) > \underline{z_j}(\Delta_j, E_l[\delta_j], \eta_j)$. From the social planner's first-order condition with respect to z_j we get:

$$z_j^*(\Delta_j, \overline{E(\delta_j)}, \eta_j) = \underbrace{\overline{z_j}(\Delta_j, \overline{E(\delta_j)}, \eta_j)}_{\text{average expectations}} + \frac{1}{\lambda K(\eta_j)} \left[\underbrace{\ln\left[\frac{\gamma^{\overline{E[\delta_j]}}\hat{E}[y_{M_j}]}{\hat{E}[y(\Delta_j)]}\right]}_{\geq 0} + \underbrace{\psi\left[\hat{E}[y(\Delta_j)] - \hat{E}[y_{M_j}]/\gamma\right]}_{>0} \right] \tag{27}$$

where $\ln\left[\frac{\gamma^{\overline{E[\delta_j]}}\hat{E}[y_{M_j}]}{\hat{E}[y(\Delta_j)]}\right] \geq 0$ holds since we can rewrite equation (23) to $\hat{E}[y_{M_j}]\gamma^{\overline{E[\delta_j]}} = \frac{1}{c}$, which, together with (14), implies $\hat{E}[y(\Delta_j)] \leq \frac{1}{c} = \gamma^{\overline{E[\delta_j]}}\hat{E}[y_{M_j}]$.
Secondly, $\psi\left[\hat{E}[y(\Delta_j)] - \hat{E}[y_{M_j}]/\gamma\right] > 0$ holds since from (14) we get that $y_j(\Delta_j) \geq y_{M_j}$ $\forall\Delta_j \in [1/2, 1]$ and we additionally have that $\gamma > 1, \psi > 0$.

A.4 Parameter Calibration - Comparative Statics

Figure A.1 plots our comparative static with respect to market size.

This section provides the parameters with which we calibrate our model in order to plot Figures 7 and A.1.

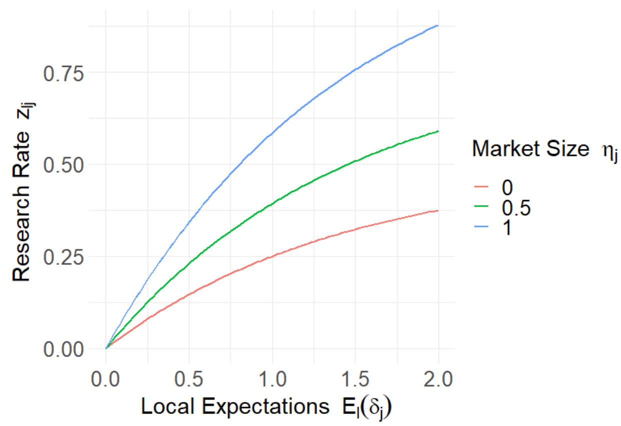


Figure A.1: Innovation Responses dependent on market size η_j

Note: The figure plots inventors' innovation response dependent on their expectations $E_l(\delta_l)$ and market size η_j.

For the purpose of our comparative statics analysis, we calibrate the model with the following parameters. In the baseline model without market size, we set the scaling constant of costs to $\kappa = 1$ and chose $\gamma = 2$. Innovation intensity, Δ_j, is varied across the representative values 0, 0.5, and 1, while local expectations $E_l(\delta_j)$ are sampled continuously over the interval $[0, 1]$. The intrinsic utility parameter μ_l is evaluated on the interval $[0, 1]$.

In the extended model that incorporates market size, we fix the innovation intensity at $\Delta_j = 0.5$ and maintain $\gamma = 2$. The market size parameter η_j is evaluated at 0, 0.5, and 1. The function $K(\eta_j)$ is calibrated as

$$K(\eta_j) = \Big(1 - 0.5 \log(1 + \eta_j)\Big)^2,$$

which provides a decreasing and concave relationship in η_j consistent with the assumption of diminishing marginal effects.

A.5 Alternative Modeling of Market Size

Instead of decreasing costs, we can also model the step-size of innovation to be increasing in the market size. The quality of a good y_j then evolves according to: $q_j = F(\Gamma(\eta_j))$, where $\Gamma_j(k) > 1$ denotes the step size of a green innovation which potentially depends on the size of the market η_j. $F(.)$ simply sums over past inventive success. When $\frac{\partial \Gamma(\eta_j)}{\partial \eta_j} > 0$ the step size increases with market size.

The privately chosen research rate in the economy is then given by:

$$z_{lj}(\Delta_j, E_l(\delta_j), \eta_j) = \frac{\Delta_j E_l\left[\pi_{Mj}\right]}{\kappa} + \frac{\mu_l}{\alpha\kappa} = \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\Gamma(\eta_j)^{E_l[\delta_j]}}\right) + \frac{\mu_l}{\alpha\kappa}. \tag{28}$$

As long as consumers somewhat value the greenness of a good $E_l(\delta_j) > 0$, the returns to innovation increase with larger step size $\Gamma(\eta_j)$. Therefore, the privately chosen research rate increases in the step size $\frac{\partial z_{lj}}{\partial \Gamma(\eta_j)} > 0 \; \forall l, j$. Together with the feature of inventors standing on the shoulders of giants $\frac{\partial \Gamma(\eta_j)}{\partial \eta_j} > 0$, this implies that the research rate increases in the size of the green market of good j. Similar to the interpretation above, this is borrowed from the literature on directed technical change, where a larger market for e.g. green goods implies higher gains from innovation in that market (see Acemoglu 2002, Acemoglu 2007, Acemoglu et al. 2012).

Assumption 2: Assume that $\Gamma(\eta_j)$ and $E_l(\delta_j)$ are reasonable small such that $E_l(\delta_j) ln(\Gamma(\eta_j)) < 1$. Intuitively, when this term is instead larger than 1, it implies that either the step size is significantly larger than $\Gamma(\eta_j) > 2$ or consumers value the quality of a good relatively more than its consumption value $\delta > 1$. $\Gamma(\eta_j) > 2$ would imply a doubling of quality with every innovation, a somewhat unrealistic proposition. Under assumption 1, we have positive cross derivatives $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial E[\delta_j]} > 0$. We can then derive a hypothesis in the same spirit as hypothesis 2.

Hypothesis 2b: In addition to assumption 2, assume the world is such that inventors stand on the shoulders of giants $\frac{\partial \Gamma(\eta_j)}{\partial \eta_j} > 0$. Then, in markets where green products are already proliferated (large η_j) inventors respond more strongly to increases in their expectation $E_l(\delta_j)$.

B Online Appendix - Empirical Analysis

This appendix provides empirical robustness checks and supplementary analyses for the main paper. It includes results verifying the robustness of findings to different technology trend controls, examines heterogeneity by technology class and subclass, explores spillover effects across neighboring regions, and tests robustness to alternative definitions of green innovation and disaster exposure. Additionally, it assesses heterogeneity based on inventor experience, disaster severity, disaster type, competition intensity, and green market size.

B.1 Alternative Estimator

To address concerns about heterogeneous treatment effects in difference-in-differences designs, we re-estimate our main green innovation results using the estimator proposed by Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024). This estimator remains valid under treatment effect heterogeneity and serves as a robustness check for our baseline specification in Equation (4).

In contrast to our preferred approach, which uses all untreated regions as controls regardless of treatment history, the alternative estimator restricts comparisons to regions with identical treatment trajectories up to period $t-1$. For example, it compares regions with two prior disasters that receive a third at time t, to regions with the same prior exposure that are not treated at t. Once a control region becomes treated, it drops out of the control group. As a result, the control group diminishes over time as more units receive treatment.

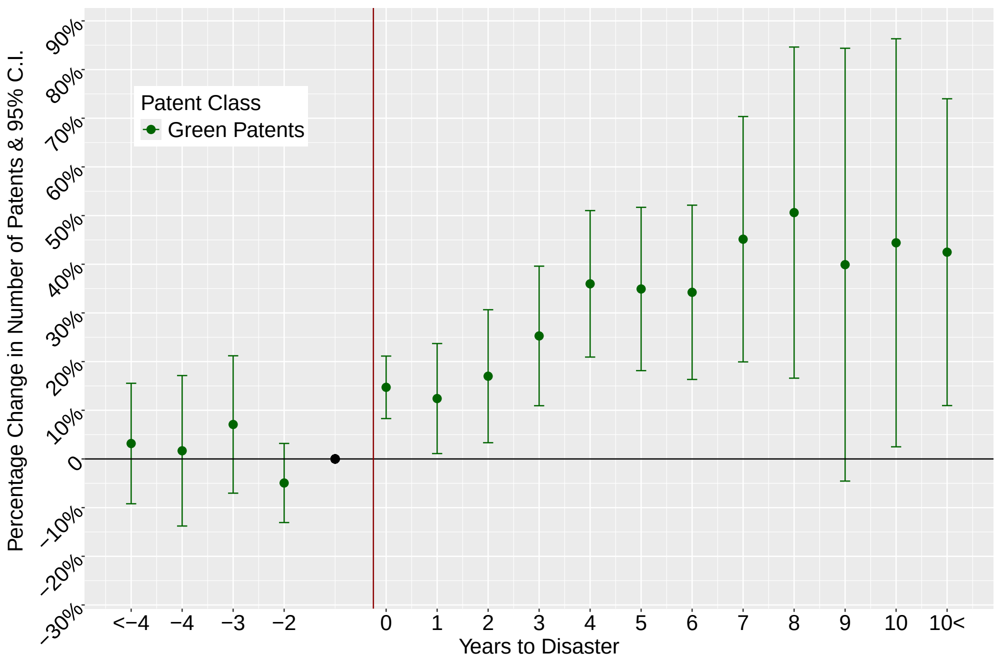


Figure B.1: Patenting following Exposure to a Natural Disaster — Estimator of Chaisemartin and D'Haultfœuille 2023; Chaisemartin and D'Haultfœuille 2024

Note: This figure depicts the results of our preferred event-study using the estimator of Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024). Standard errors are clustered at the region level, and confidence intervals are drawn for the 95% interval.

The resulting estimates (Figure B.1) are somewhat larger and more persistent than those from our baseline model (Figure 3). This is encouraging, as it suggests that our findings are not an artifact of bias introduced by treatment effect heterogeneity. However, the alternative estimator also introduces trade-offs. The shrinking control group reduces statistical power in later event periods, and the restriction to regions with identical treatment histories may limit generalizability.

While it is not entirely clear which approach is more suitable in our context, the qualitative similarity across both estimators increases confidence in the robustness of our results. The alternative estimator offers protection against heterogeneity bias, while our preferred specification leverages a broader and more interpretable sample. Taken together, the results from both approaches point to a consistent and significant relationship between disaster exposure and green innovation. Given that the TWFE specification produces more conservative estimates and facilitates clearer interpretation, we retain it as our primary approach in the main analysis.

B.2 Patenting Results without Technology Trend Controls

For most of our analysis, we control for the time-varying regional shares in patenting from different technology classes CPC_{lt}. In the long run, these shares might be themselves affected by natural disaster exposure. For the sake of robustness, we reestimate our baseline specification without controlling for technology trends. Figure B.2 plots the results of our event-study specification (4) without controlling for technology trends CPC_{lt}. Results are nearly identical to those in Figure 3.

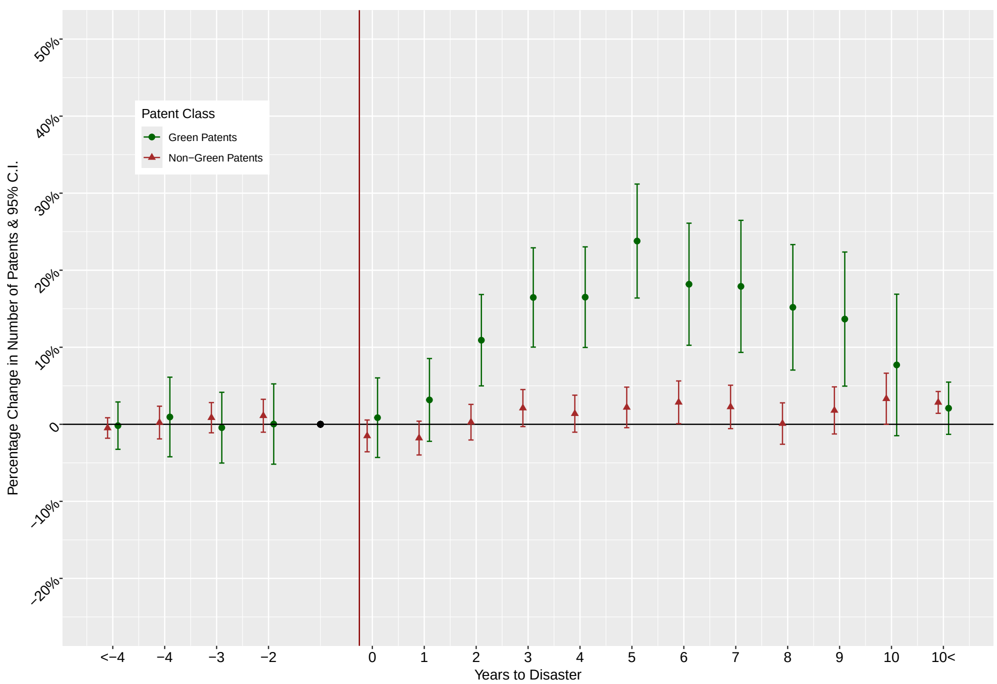
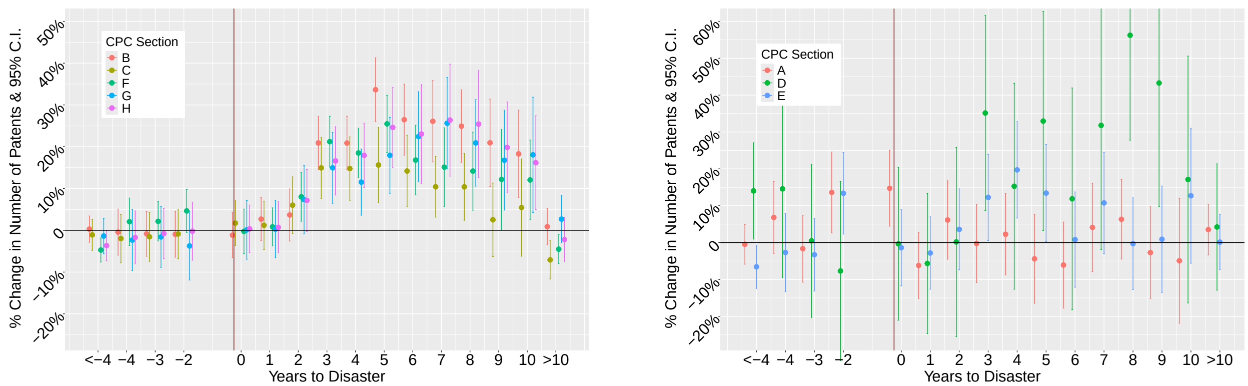


Figure B.2: Patenting following exposure - without technology trends

Note: This figure depicts the results for our baseline event-study specification, where we compare patenting in regions exposed to natural disasters to unaffected regions. We drop the technology trend controls. We plot one regression for green and one for non-green patents. The sample average of green patents per year per region is 2.54, while the sample average of non-green patents is 30.5. These numbers correspond to the respective denominator for green and non-green patents in equation (3). Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

B.3 Green innovation by technology class

In this section of the appendix, we examine whether the baseline effect of natural disasters on green innovation is concentrated in particular technological domains or reflects a broader pattern across fields. To this end, we replicate our baseline green innovation event study specification separately by broad technology/CPC class. Panel A in Figure B.3 shows



(a) Effects for CPC classes B,C,F,G,H

(b) Effects for CPC classes A,D,E

Figure B.3: Green innovation response to natural disaster by technology class

Note: This Figure depicts the effects of natural disaster exposure on green patenting for patents from different technology classes (1-digit CPC classes). The mean number of green patents in CPC classes is as follows: A: 0.114, B: 0.451, C: 0.477, D: 0.054, E: 0.102, F: 0.766, G: 0.221, H: 0.550. Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

results for classes B (Performing Operations; Transporting), C (Chemistry; Metallurgy), F (Mechanical Engineering; Lighting; Heating), G (Physics), and H (Electricity). These classes closely mirror the baseline response in both timing and magnitude, exhibiting a smooth and persistent increase in green patenting following disasters. This consistency suggests that the average effect is not driven by any single technological area.

Panel B in Figure B.3 presents results for classes A (Human Necessities), D (Textiles; Paper), and E (Fixed Constructions), where greater heterogeneity is observed. Class D shows particularly large and volatile effects, while class E remains broadly aligned with the baseline pattern, albeit with more noise. Class A is the most distinct, possibly reflecting the different dynamics of green innovation in agriculture and related fields.

Taken together, these results indicate that the positive innovation response to disasters is not confined to a narrow set of technologies, but is instead distributed across a wide range of broad CPC classes.

B.4 Subclasses of Y02

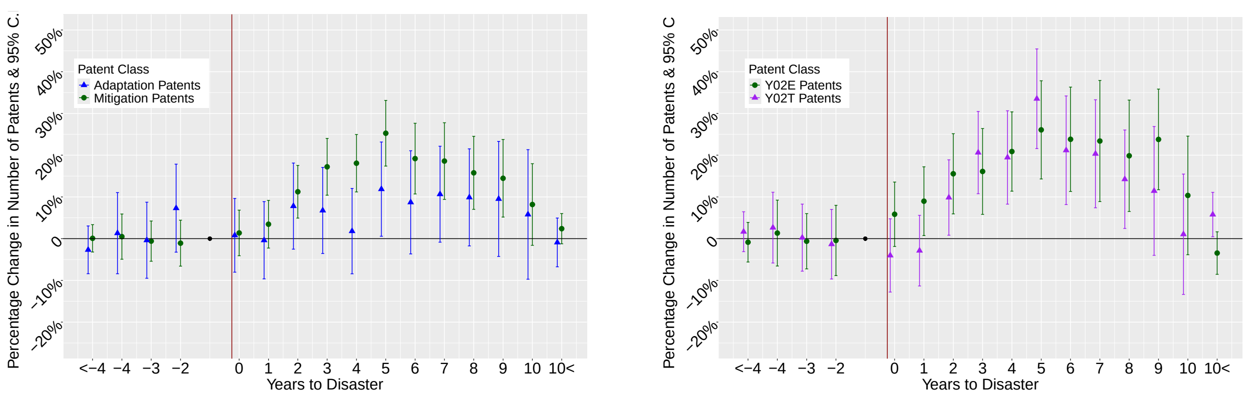
Our results suggest that natural disasters are a robust and broad-based driver of green innovation. This has important implications for understanding the determinants of environmental technological change, as it indicates that external shocks can meaningfully stimulate patenting activity across a diverse set of green technology fields.

We can split our sample further by a patents respective “green subclass”. See Table B.1 for these subclasses.

Class	Description
Y02A	Climate change mitigation technologies related to agriculture, forestry, or land use
Y02B	Climate change mitigation technologies related to buildings, e.g., housing, appliances, or related end-user applications
Y02C	Capture, storage, sequestration, or disposal of greenhouse gases
Y02D	Climate change mitigation technologies in information and communication technologies (ICT), aiming at reducing ICT-related energy use
Y02E	Reduction of greenhouse gas (GHG) emissions related to energy generation, transmission, or distribution
Y02P	Climate change mitigation technologies in the production or processing of goods
Y02T	Climate change mitigation technologies related to transportation
Y02W	Climate change mitigation technologies related to wastewater treatment or waste management

Table B.1: Y02 subclasses of climate change mitigation technologies

In Table 2 and Figure B.4a we pool subclasses Y02B-Y02W into mitigation technologies. Figure B.4a depicts our results when estimating (4) on the split sample of adaptation and mitigation technologies.



(a) Patenting in Mitigation and Adaptation

(b) Patenting in Y02E and Y02T subclasses

Figure B.4: Green innovation patterns in Germany and France by technology focus

Note: **Left panel:** Each time we split the sample to only contain technologies from the respective CPC class(es). Therefore the figure depicts 2 separate regressions. The sample average of mitigation patents is 2.323, while the sample average of adaptation patents is 0.2256. **Right panel:** This figure plots our baseline specification, when only looking at the Y02E and Y02T subclasses. The sample average of Y02E patents is 0.885, while the sample average of Y02T patents is 0.933. Standard errors are clustered on the region level and confidence intervals are drawn for the 95% interval.

In Table B.2, we report estimates of the effect of natural disaster exposure on different Y02 green patent subclasses. The outcome variables are subclass-specific indicators for green patent filings, and the main regressor is the cumulative count of natural disasters over the past five years. Each column represents a separate regression. All models include country-year fixed effects, region fixed effects, and CPC-class controls.

We find consistently positive and statistically significant effects across all Y02 subclasses. The estimated coefficients are significant at the 1% level in all cases and vary in magnitude. The largest effects are observed in Y02D (energy generation, coefficient = 0.265), Y02C (carbon capture and storage, coefficient = 0.178), and Y02B (building technologies, coefficient = 0.137), indicating particularly strong responsiveness in domains most directly tied to energy systems and emissions mitigation.

Transport (Y02T) and energy conservation (Y02E) technologies, while not associated with the largest coefficients, are notable for their relatively high baseline levels of patenting activity and their relevance to energy-saving policy goals. Given their substantive importance and distinct temporal dynamics, we present separate event-study plots for these subclasses in Appendix Figure B.4b.

Taken together, these results demonstrate that the innovation response to natural disasters is not confined to a narrow subset of green technologies, but rather operates across a wide range of sectors—with particularly strong effects in energy-related and emissions-reducing fields. This underscores the role of natural disasters as a catalyst for environmentally beneficial technological change.

Table B.2: Regression by Y02 subclass

	Dependent variable:							
	Y02A	Y02B	Y02C	Y02D	Y02E	Y02P	Y02T	Y02W
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative Count	0.044***	0.137***	0.178***	0.265***	0.084***	0.077***	0.088***	0.042***
	(0.013)	(0.016)	(0.047)	(0.044)	(0.014)	(0.016)	(0.012)	(0.015)
Country-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample Means	0.226	0.251	0.036	0.075	0.885	0.425	0.933	0.152
Observations	15,813	15,813	15,813	15,813	15,813	15,813	15,813	15,813
R^2	0.513	0.486	0.363	0.462	0.628	0.641	0.611	0.421
Adj. R^2	0.487	0.459	0.329	0.433	0.609	0.622	0.590	0.390

Note: This table reports the results of our baseline difference-in-differences regression for different subclasses of green patents. We report results for all subclasses of Y02. Sample Means gives the respective sample means per region-year for these subclasses. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

B.5 Most Severe-Disaster Severity

We use EM-DAT data to identify each region's most severe natural disaster, defined as the event with the highest recorded number of deaths. We then construct a treatment indicator that equals one in all years following the region's most deadly disaster. This specification restricts treatment to occur at most once per region and allows us to implement the staggered adoption event-study estimator of Sun and Abraham (2021), which is designed for settings where treatment is irreversible and varies in timing.

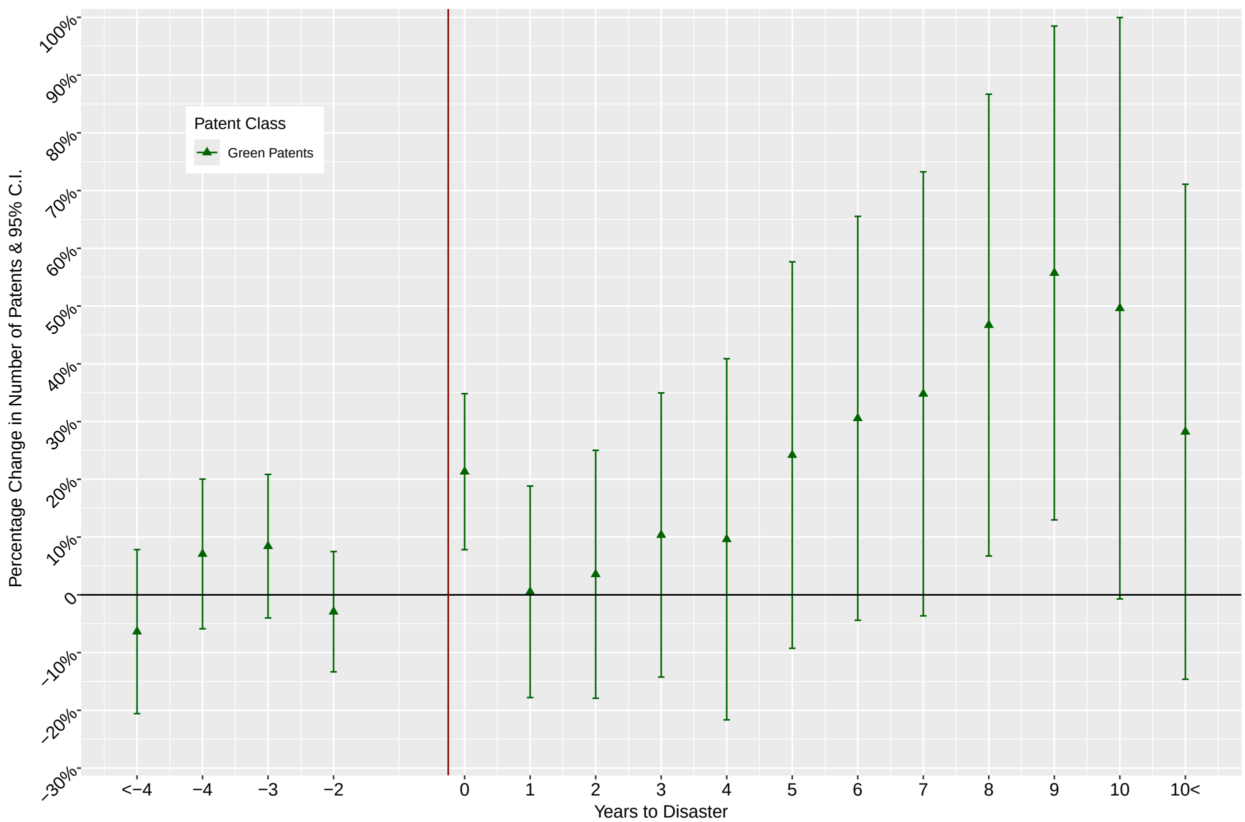


Figure B.5: Patenting following the Exposure to the Most Severe Natural Disaster

Note: This figure plots green patenting after the most severe disaster, as measured by deaths, in our sample. We estimate effects using the estimator of Sun and Abraham (2021). Standard errors are clustered at the region level, and 95% confidence intervals are shown.

Figure B.5 shows the resulting event-study estimates. The identifying variation in this setting comes from comparing regions that have already experienced their most severe disaster to those that have not yet done so. Because treatment is limited to a single (and extreme) event per region, we reduce concerns about overlapping or serially correlated shocks. At the same time, this comes at the cost of substantially reduced variation, which leads to increased standard errors and greater noisiness in the estimated effects.

Despite the reduced statistical precision, we find that the most severe disasters are associated with stronger innovation responses than in our baseline specification. However, the effect is more delayed, with increases in green patenting becoming visible only several years after the event.

B.6 Disaster Type

Figure B.6 plots our event-study estimates separately for each disaster type: extreme temperature, flood, and storm. This breakdown allows us to explore potential heterogeneity in the innovation response depending on the nature of the shock.

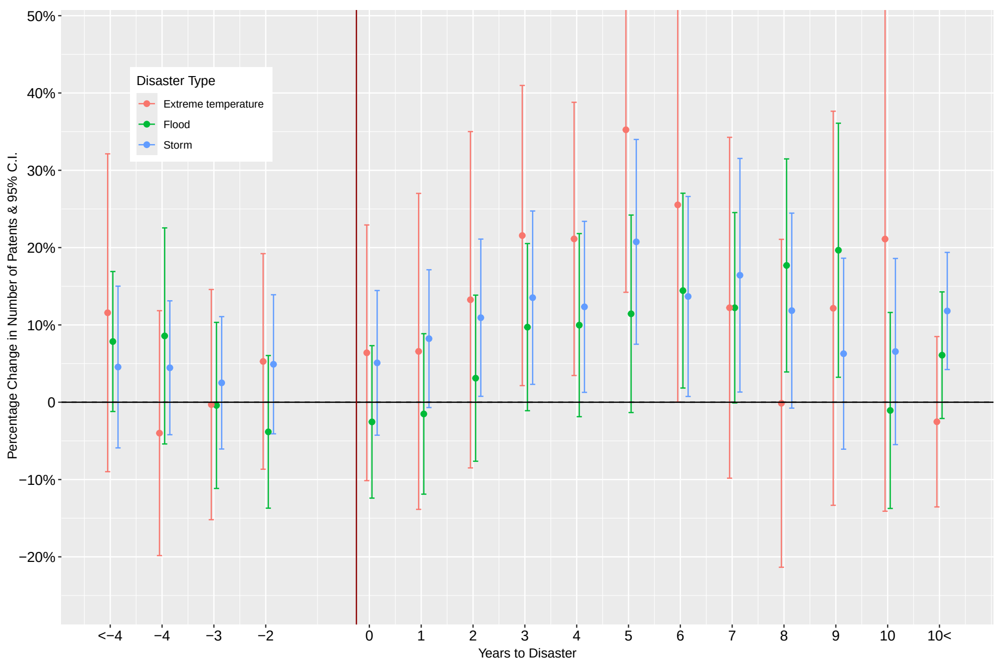


Figure B.6: Green Patenting Following Different Disaster Types

Note: This figure presents event-study estimates for the impact of three different disaster types—extreme temperature, flood, and storm—on green patenting. We omit droughts, as there are not enough droughts (3) in our sample to plot meaningful estimates. Confidence intervals correspond to the 95% level, and standard errors are clustered at the region level.

While the estimates are noisier due to the smaller number of observations for each disaster category, the overall patterns are consistent with our main findings in Figure 3. In all three cases, we observe a notable increase in green patenting activity in the years following disaster exposure. This supports our interpretation that natural disasters act as catalysts for environmentally oriented innovation, regardless of the specific type of event.

These results suggest that the mechanism linking disaster exposure to innovation is not driven by one specific type of shock, but appears to hold more generally across a range of climate-related events.

B.7 Spillovers - Alternative Modeling

Table B.3 depicts alternative sample restrictions compared to Table 3 in the main text. In columns (1)–(3) we exclude regions affected in the past 3 years, (4)–(6) in the past 4 years, (7)–(9) in the past 6 years, and (10)–(12) in the past 7 years. The more regions we remove, the smaller our sample size comes. We do so as to not have affected regions in our control group. Overall the results for spillovers from regions that are 100km or 150km remain largely the same. However, when we remove all regions that were affected in the past 6 or 7 years, we find somewhat larger effects of natural disasters in regions closer than 50km away.

Table B.4 presents regression results examining the spillover effects of neighboring disasters using an unrestricted sample that includes regions directly affected by disasters. The estimates are disaggregated by distance thresholds of 50km, 100km, and 150km. At the 50km threshold (column 1), the effect of cumulative neighboring disasters is positive and statistically significant, with a coefficient of 0.0109. For the 100km and 150km thresholds (columns 2 and 3), the coefficients are negative. This is due to the control group now containing regions that are affected by natural disasters. We essentially invert treatment and control group.

Table B.3: Spillovers of Neighboring Disasters - Alternative Windows

	Dependent variable: $P(Y02_{lt})$											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Cumulative Count (50km)												
Neighboring Disasters	0.0101***			0.0098***			0.0143***			0.0271**		
	(0.0032)			(0.0032)			(0.0050)			(0.0107)		
Cumulative Count (100km)												
Neighboring Disasters		0.00005			−0.0003			0.0005			0.0006	
		(0.0005)			(0.0005)			(0.0006)			(0.0006)	
Cumulative Count (150km)												
Neighboring Disasters			−0.0004			−0.0006*			−0.0002			−0.0001
			(0.0004)			(0.0003)			(0.0004)			(0.0004)
Country-Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,464	5,464	5,464	4,680	4,680	4,680	3,704	3,704	3,704	3,309	3,309	3,309
R^2	0.8421	0.8414	0.8415	0.8546	0.8540	0.8541	0.8460	0.8449	0.8449	0.8515	0.8502	0.8501
Adjusted R^2	0.8153	0.8145	0.8146	0.8251	0.8244	0.8246	0.8120	0.8106	0.8106	0.8176	0.8159	0.8159

Note: This table gives the results of our spillover analysis for different samples dependent on regions past natural disaster exposure. We exclude all regions with past disaster exposure for different time windows. In columns (1)–(3) we exclude regions affected in the past 3 years, (4)–(6) in the past 4 years, (7)–(9) in the past 6 years, and (10)–(12) in the past 7 years. The more regions we remove, the smaller our sample size becomes. “Cumulative Count Neighboring Disasters” is the count of past natural disasters in neighboring regions. Which regions are considered as “neighbors” depends on the distance threshold as shown in Figure 4. Standard errors are clustered on the region level and are reported in parentheses. P-values: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B.4: Spillovers of Neighboring Disasters - Unrestricted Sample

	Dependent variable:		
	$P(Y02_{lt})$		
	(1)	(2)	(3)
Cumulative Count (50km) Neighboring Disasters	0.0109^{***} (0.0025)		
Cumulative Count (100km) Neighboring Disasters		-0.0018^{***} (0.0003)	
Cumulative Count (150km) Neighboring Disasters			-0.0014^{***} (0.0002)
Country-Year F.E.	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes
Observations	15,813	15,813	15,813
R^2	0.7376	0.7374	0.7378
Adjusted R^2	0.7236	0.7234	0.7238

Note: This table gives the estimates of our spillover analysis when we do not constain the sample. Thus all regions, regardless of past exposure, are in the sample. Standard errors are clustered at the region level and reported in parentheses. We do not remove themselves affected regions from the sample. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B.8 Reasons to Innovate Robustness

To assess the robustness of our baseline survey results (Table 6), we estimate two alternative specifications that sequentially incorporate more granular regional fixed effects. Table B.5 includes NUTS-2 fixed effects to control for unobserved time-invariant characteristics at a broader regional level, while Table B.6 introduces NUTS-3 fixed effects.

Table B.5: Effect of Cumulative Disaster Count on Reasons to Innovate (Robustness Check NUTS-2)

	Dependent variable:					
	Expected Regulation (1)	Expected Demand (2)	Existing Regulation (3)	Public Funding (4)	Voluntary Standard (5)	Reputation (6)
Cumulative Count	3.66***	1.72***	2.89***	1.22**	2.43***	0.263
	(0.582)	(0.497)	(0.569)	(0.499)	(0.563)	(0.745)
Firm Size F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E. (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-2 F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.6333	0.5564	0.4066	0.4907	0.5795	0.6147
Observations	8,787	8,754	8,862	8,776	8,782	5,423
R^2	0.554	0.492	0.610	0.422	0.547	0.670
Adj. R^2	0.548	0.485	0.605	0.414	0.541	0.663

Note: This table reports the effect of disaster exposure on the drivers of innovation as measured in the survey. One additional past disaster increases the probability of a firm mentioning these factors by β percentage points. Each column reports coefficients from separate regressions. Outcomes are: Expected Regulation = expected future environmental rules; Expected Demand = expected future market demand for green innovation; Existing Regulation = current environmental rules/charges; Public Funding = government grants/subsidies; Voluntary Standard = voluntarily joining a standard for green practices (e.g. environmental/organic label); Reputation = firm's reputation concerns. Coefficients and standard errors are scaled by 100 for interpretability as percentage point effects. "Cumulative Count" captures disaster exposure. Standard errors clustered at the region (Kreis, NUTS-3) level. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Across both specifications, the direction of the estimated coefficients on cumulative disaster exposure remains qualitatively consistent with the baseline, indicating that the underlying relationship is robust. However, once NUTS-3 fixed effects are included, the magnitude of estimated effects is similar, but statistical significance weakens in several cases. This reduction in significance likely reflects the limited within-region variation available across just three survey waves, which constrains identification when highly granular fixed effects are introduced. Nonetheless, the overall pattern provides reassurance that the baseline results are not driven by omitted regional heterogeneity.

B.8.1 French Research Funding

To explore whether changes in public research funding explain the increase in green innovation after natural disasters, we draw on ScanR, an administrative database developed by

Table B.6: Effect of Cumulative Disaster Count on Reasons to Innovate (Robustness Check NUTS-3)

	Dependent variable:					
	Expected Regulation (1)	Expected Demand (2)	Existing Regulation (3)	Public Funding (4)	Voluntary Standard (5)	Reputation (6)
Cumulative Count	2.50**	0.852	1.52	1.15	1.85	1.21
	(1.25)	(1.05)	(1.03)	(0.893)	(1.30)	(0.904)
Firm Size F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E. (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-3 F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Y	0.6333	0.5564	0.4066	0.4907	0.5795	0.6147
Observations	8,787	8,754	8,862	8,776	8,782	5,423
R^2	0.574	0.515	0.629	0.451	0.566	0.694
Adj. R^2	0.550	0.487	0.608	0.419	0.542	0.665

Note: This table reports the effect of disaster exposure on the drivers of innovation as measured in the survey. One additional past disaster increases the probability of a firm mentioning these factors by β percentage points. Each column reports coefficients from separate regressions. Outcomes are: Expected Regulation = expected future environmental rules; Expected Demand = expected future market demand for green innovation; Existing Regulation = current environmental rules/charges; Public Funding = government grants/subsidies; Voluntary Standard = voluntarily joining a standard for green practices (e.g. environmental/organic label); Reputation = firm's reputation concerns. Coefficients and standard errors are scaled by 100 for interpretability as percentage point effects. "Cumulative Count" captures disaster exposure. Standard errors clustered at the region (Kreis, NUTS-3) level. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

the French Ministry of Higher Education, Research, and Innovation.[25] The platform lists 121,451 publicly funded research projects initiated in France between 1999 and 2023, including funding from Horizon 2020/Horizon Europe, the French National Research Agency (ANR), and the Hubert Curien Partnership (PHC). We restrict the data to projects launched before 2019 to align with the period for which we observe disaster exposure.

We aggregate project-level information to the region-year level and construct two outcome measures: (1) the count of distinct research funding streams and (2) the total research budget per region-year. We then match this data to natural disaster exposure and estimate difference-in-differences regressions with region and year fixed effects, controlling for CPC technological structure.

Table B.7 reports the results. Across specifications, we find no statistically significant effects of disaster exposure on either the number of funded projects or the total research budget. Both cumulative and recent disaster exposure are unrelated to regional research funding outcomes. These results rule out selective increases in public R&D support as the primary mechanism behind our main findings.

[25] `https://scanr.enseignementsup-recherche.gouv.fr/`

Table B.7: French Research Funding

	Dependent variable:			
	Count	Budget	Count	Budget
	(1)	(2)	(3)	(4)
Cumulative Count	0.254	−1,224k		
	(0.385)	(1,248k)		
Disaster Count Last 3 Years			−0.365	−165k
			(0.325)	(1,228k)
Year f.e.	Yes	Yes	Yes	Yes
Region f.e.	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes
Observations	2,848	2,848	2,848	2,848
R^2	0.309	0.106	0.309	0.105
Adj. R^2	0.257	0.038	0.256	0.037

Note: This table reports results for different measures research funding. In columns (1) and (3) we report results on the number of funding allocations to a region, while in columns (2) and (4) we report results on the amount of funding allocated to a region. Cumulative count is the count of past natural disasters. "Disaster Count Last 3 Years" is the count of natural disasters in the past 3 years. We only have research funding data for France. Standard errors are clustered on the region level and are reported in parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

B.9 Alternative Measures of Green Innovation Robustness

Our green product variable is derived from a survey question that asks: "During [the past two years], did your enterprise introduce new products or services with the following environmental benefits through the use of these products/services, and if yes, what was their contribution to environmental protection The survey lists the following four benefits: (a) reduced energy use, (b) reduced air, water, soil, or noise pollution, (c) improved recycling of products after use, and (d) extended product life through longer-lasting, more durable products. Respondents could answer with "Yes, significant", "Yes", insignificant, and "No" for each of the four benefits. In our analysis, the dummy variable for Green Products is assigned a value of one if a firm indicated that it has introduced a new product or service encompassing any of the four environmental benefits, regardless of whether that benefit was deemed significant or insignificant. Our within-firm green innovation indicator is based on the following survey question: "During [the past two years], did your enterprise introduce innovations that had any of the following environmental benefits, and if yes, was their contribution to environmental protection rather significant or insignificant?". The survey lists the following benefits (a) reduced energy use per unit of output, (b) reduced material use/

use of water per unit of output, (c) reduced CO2 footprint (total CO2 production), (d) reduced air pollution, (e) reduced noise pollution, (f) replaced fossil energy sourced by renewable energy sources, (g) replaced materials by less hazardous substitutes, (h) recycled waste, water, or materials for own use or sale. Firms could again indicate "Yes", significant, "Yes", insignificant, and "No" for each of the four benefits. For our analysis, the within-firm green innovation indicator equals one if a firm has introduced an innovation with any of the mentioned (significant or insignificant) benefits.

Table B.8 provides additional robustness for our results reported in Table 5, which examine the effect of cumulative natural disaster exposure on survey green innovation outcomes and perceived climate affectedness. While Table 5 includes controls for firm size, revenue, industry, and year, it does not include region fixed effects. To provide additional robustness, Table B.8 introduces regional fixed effects at two levels: columns (1)–(4) include NUTS-2 fixed effects, while columns (5)–(7) include NUTS-3 fixed effects. The direction and relative magnitude of the coefficients on cumulative disaster count remain qualitatively consistent across specifications. As in earlier robustness checks, the decline in statistical significance in the NUTS-3 specification is attributable to reduced statistical power due to limited within-region variation across the three available waves. Since climate affectedness is only elicited in one wave, we can not include NUTS-3 fixed effects, as this is the level of our variation.

Table B.8: Effect of Cumulative Disaster Count on Green Innovation and Climate Affectedness (Robustness Regional Fixed Effects)

	Green Innovation Outcomes			Climate	Green Innovation Outcomes		
	Green Innovation	Within-firm	Green Products	Affectedness	Green Innovation	Within-firm	Green Products
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cumulative Count	6.59***	5.75***	4.37***	10.7***	3.22	2.78	2.25*
	(0.702)	(0.640)	(0.532)	(0.968)	(2.08)	(1.80)	(1.18)
Firm Size F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	No (Single Wave)	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-2 F.E.	Yes	Yes	Yes	Yes	No	No	No
NUTS-3 F.E.	No	No	No	No	Yes	Yes	Yes
Observations	15,395	15,426	15,226	4,873	15,395	15,426	15,226
R^2	0.638	0.599	0.457	0.597	0.653	0.614	0.475
Adj. R^2	0.635	0.596	0.453	0.588	0.642	0.602	0.458

Note: This table presents robustness checks for green innovation outcomes. Coefficients and standard errors are multiplied by 100 to reflect percentage point effects. All models include firm size (based on employment), revenue controls, year fixed effects, and 2-digit NACE industry fixed effects. We either include NUTS-2 (Bezirk) or NUTS-3 (region) level fixed effects. Standard errors are clustered at the regional (Kreis) level. Significance levels: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

B.10 Alternative Competition Windows

Table B.9 presents the results from using alternative time windows to compute competition intensity—specifically, using either a 1-year or 3-year window before the patent filing year. This table complements the baseline analysis in Section 6.2.1 and the corresponding estimates in Table 7, where competition is measured as the average of the filing year and the year prior.

Qualitatively, the results remain consistent: the innovation response to natural disaster exposure is concentrated in the high-competition group, while the low-competition group shows no significant effect. However, the estimated coefficients in the high-competition groups (columns 1 and 3) are slightly smaller than in the baseline (Table 7, column 1), and the Wald test p-values are larger—0.1363 for the 1-year window and 0.054* for the 3-year window—compared to 0.0365** in the baseline. This difference is primarily due to less precise estimates in the low-competition subsamples (columns 2 and 4), as reflected in their larger standard errors. Overall, while the alternative competition windows yield attenuated statistical significance, the direction and relative magnitude of the effects remain stable, providing additional support for the robustness of our findings.

Table B.9: Competition Split Above/Below Median

	Dependent variable:			
	$P(Y02_{lt})$			
	1 Year - High Competition	1 Year - Low Competition	3 Year - High Competition	3 Year - Low Competition
	(1)	(2)	(3)	(4)
Cumulative Count	0.090***	0.035	0.099***	0.003
	(0.023)	(0.031)	(0.029)	(0.029)
Country-Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes
P Value	0.1363		0.054*	
Sample Means	1.8046	1.382	2.0166	1.3536
Observations	9,036	9,036	7,530	7,530
R^2	0.626	0.513	0.706	0.590
Adj. R^2	0.591	0.467	0.672	0.542

Note: This table reports the results for our test of the model's comparative statics with regard to competition. Columns (1)-(2) measures competition based on the prior year, while columns (3)-(4) based on the last 3 years piror to patent filing. Cumulative count is the count of past natural disasters. The Wald-tests examine if the coefficient for cumulative disaster count significantly differs between splits. We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})^2}{\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})}$, where: $\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}}) = \text{Var}(\hat{\beta}_{\text{eq1}}) + \text{Var}(\hat{\beta}_{\text{eq2}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq1}}, \hat{\beta}_{\text{eq2}})$. Standard errors are clustered at the region level and reported in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

B.11 Alternative Green Good Window

Table B.10 presents results from using alternative time windows to compute the green product share in each industry. Specifically, we calculate the share based on either the filing year alone (1-year window) or the filing year and the two preceding years (3-year window). These results relate to Section 6.2.2 in the main text and serve as a robustness check for our baseline findings in Table 7, where the green share is calculated using a 2-year window.

The results are remarkably stable across specifications. Across all windows, inventors in greener industries—defined as those above the median green product share—respond more strongly to natural disaster exposure than those in less green industries. The coefficients remain positive and highly significant for both high- and low-greenness groups, with larger point estimates consistently observed in the above-median sample. Compared to the baseline 2-year window (Table 7), the cumulative count coefficients for the above-median groups in both the 1-year and 3-year windows are nearly identical (0.088^{***} and 0.087^{***}, respectively). Likewise, the Wald test p-values remain below conventional significance thresholds: 0.0398^{**} for the 1-year window and 0.0397^{**} for the 3-year window, compared to 0.0307^{**} in the baseline. This consistency confirms that our results are not sensitive to the specific choice of window for measuring green market size.

Taken together, these findings reinforce our interpretation that market conditions—specifically the size of the green goods market—shape inventors' responsiveness to climate-related shocks. The robustness of the result across time windows strengthens the credibility of this mechanism.

Table B.10: Green Product Split by Median

	Dependent variable:			
	$P(Y02_{lt})$			
Greenness Cutoff:	1 Year Window Above Median	1 Year Window Below Median	3 Year Window Above Median	3 Year Window Below Median
	(1)	(2)	(3)	(4)
Cumulative Count	0.088***	0.066***	0.087***	0.062***
	(0.011)	(0.009)	(0.009)	(0.009)
Country-Year F.E.	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes
Wald-test p-value:	0.0398**		0.0397**	
Sample Mean	1.2949	1.287	1.3617	1.3617
Observations	15,060	15,060	13,554	13,554
R^2	0.613	0.776	0.636	0.799
Adj. R^2	0.591	0.763	0.614	0.786

Note: This table reports the results for our test of the model's comparative statics with regard to the size of the green good market. In columns (1) and (2), for each industry, we calculate the average green product share over the present year. In columns (3) and (4), for each industry, we calculate the average green product share over the last 3 years. Cumulative Count is the count of past natural disasters. Results are for the years 1995–2014 in columns (1) and (2) and for the years 1997–2014 in columns (3) and (4). We only have PRODCOM data starting in 1995, so a 3-year window allows us to estimate results starting in 1997. We test the null hypothesis that the Disaster Count coefficient is larger for our sample of above-median competition patents than for our sample of below-median competition patents. We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})^2}{\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})}$, where: $\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}}) = \text{Var}(\hat{\beta}_{\text{eq1}}) + \text{Var}(\hat{\beta}_{\text{eq2}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq1}}, \hat{\beta}_{\text{eq2}})$. We can reject the Null hypothesis H_0 : $\beta_h = \beta_l$ against the alternative ($H_1 : \beta_h > \beta_l$) with the reported p value. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

B.12 First Time & Repeat Inventors

Table B.11 shows our results when we split the sample of patents based on an inventor having previously patented or not. Both reapeat and first-time inventors react to natural disaster exposure, with the effects being significantly larger for repeat inventors. Overall, there are more inventors that have previously patented than first time inventors in our sample. We denote a patent as coming from a repeat inventor if at least one of the inventors on that patent has previously patented.

Table B.11: Response by First Time & Repeat Inventors

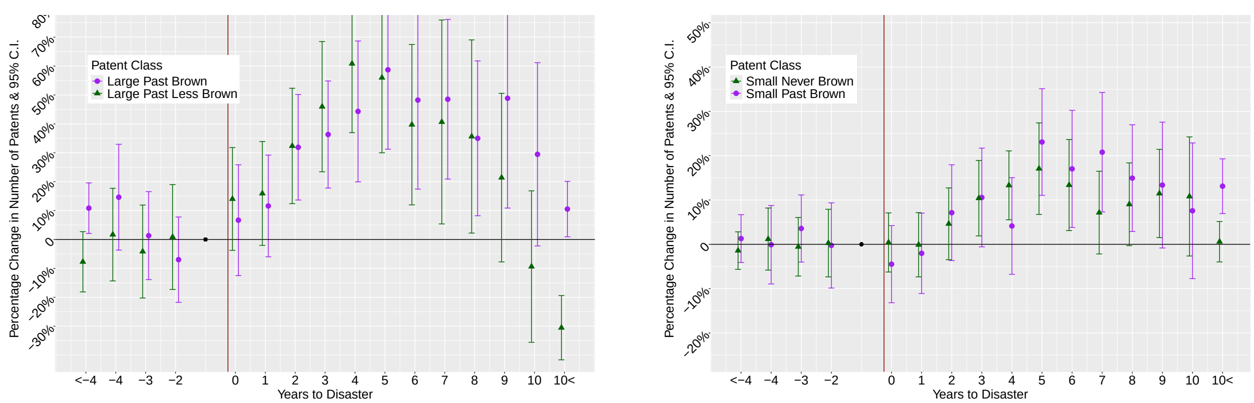
	Dependent variable:	
	$P(Y02_{lt})$	
	First-Time	Repeat Inventors
	(1)	(2)
Cumulative Count	0.050***	0.097***
	(0.016)	(0.010)
Country-Year F.E.	Yes	Yes
Region F.E.	Yes	Yes
CPC Controls	Yes	Yes
P Value	0.0129**	
Sample Means	0.1682	2.0954
Observations	15,813	15,813
R^2	0.345	0.703
Adj. R^2	0.310	0.687

Note: This table reports our results when we split the sample of inventors into First-Time and Repeat inventors. Cumulative Count is the count of past natural disasters. We test the null hypothesis that the Disaster Count coefficient is different for our sample of first-time inventors than for our sample of repeat inventors. We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})^2}{\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}})}$, where: $\text{Var}(\hat{\beta}_{\text{eq1}} - \hat{\beta}_{\text{eq2}}) = \text{Var}(\hat{\beta}_{\text{eq1}}) + \text{Var}(\hat{\beta}_{\text{eq2}}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq1}}, \hat{\beta}_{\text{eq2}})$. We can reject the Null hypothesis $H_0 : \beta_h = \beta_l$ against the alternative ($H_1 : \beta_h \neq \beta_l$) with the reported p value. Standard errors are clustered on the region level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

Our findings in Table B.11 indicate that the innovation response to natural disasters operates along both the extensive and intensive margins. We observe significant increases in green patenting among first-time inventors as well as among those with prior patenting experience, suggesting that disasters not only induce additional activity from established innovators but also bring new inventors into the green innovation space. This broad-based response reinforces the main result that environmental shocks stimulate green technological effort across the innovation spectrum.

B.13 Past Patenting

In this appendix section, we examine whether the baseline effect of natural disasters on green innovation varies with inventors' patenting histories. To do so, we split our sample along two dimensions. First, we classify patents based on the share of green patents previously filed by their inventors or firms. However, many patent holders in our dataset have no prior patent history, preventing us from directly calculating their past green patent shares. To address this limitation, we introduce a second classification based on the total number of patents previously filed by inventors. For inventors in the top quartile of past patent filings, we can reliably calculate their share of past green patents. For inventors below the top quartile, we instead check whether any inventor on a patent previously filed a clearly defined "brown" patent—one associated explicitly with environmentally harmful technologies. We adopt this definition of "brown" patents from Dechezleprêtre et al. (2021).



(a) Effects for Large Patent Filers

(b) Effects for Small Patent Filers

Figure B.7: Green innovation response to natural disaster by past patenting

Note: This figure shows the effects of natural disaster exposure on green patenting, split according to inventors' past patenting patterns. Panel (a) depicts patenting responses by inventors in the top quartile of past patent filings. Within this group, we further distinguish between those whose past patent portfolios contain an above-median share of brown patents ("Large Past Brown") and those with a below-median share of brown patents ("Large Past Less Brown"). Panel (b) depicts responses by inventors below the top quartile ("Small Patent Filers"), differentiating between those who have previously filed at least one brown patent and those who have never filed a brown patent. Brown patents are defined following the classification by Dechezleprêtre et al. (2021). Standard errors are clustered at the region level, and confidence intervals represent the 95% level.

The effects observed across these classifications indicate fairly similar responses for both "past brown" and "past less brown" inventor groups. However, among large patent filers (top quartile), inventors classified as "past less brown" exhibit somewhat less persistence in their response compared to their counterparts with extensive past brown patenting. In general, large past filers demonstrate stronger innovation responses following natural disaster exposure relative to smaller past filers.

C Online Appendix - Data

C.1 Countries in the CompNet Dataset

Table C.1 shows the time span for which different countries are available in the 9th vintage of the CompNet database (CompNet 2022). The information is directly taken from the CompNet website `https://www.comp-net.org/`.

Country	All firms	20e	Time Span
Belgium	x	x	2000 – 2020
Croatia	x	x	2002 – 2021
Czech Republic	x	x	2005 – 2020
Denmark	x	x	2001 – 2020
Finland	x	x	1999 – 2020
France	x	x	2003 – 2020
Germany		x	2001 – 2018
Hungary	x	x	2003 – 2020
Italy	x	x	2006 – 2020
Latvia*	x	x	2007 – 2019
Lithuania*	x	x	2000 – 2020
Malta	x	x	2010-2020
Netherlands	x	x	2007 – 2019
Poland		x	2002 – 2020
Portugal	x	x	2004 – 2020
Romania		x	2005 – 2020
Slovakia		x	2000 – 2020
Slovenia	x	x	2002 – 2021
Spain	x	x	2008 – 2020
Sweden	x	x	2003 – 2020
Switzerland	x	x	2009 – 2020
United Kingdom		x	1997 – 2019

Table C.1: Comp Net TimpeSpans

C.2 Community Innovation Survey

We use data from the German part of the Community Innovation Survey, the Mannheimer Innovationspanel, administered by the ZEW – Leibniz Centre for European Economic Research (ZEW - Leibniz Centre for European Economic Research n.d.). Detailed information is available at: `https://www.zew.de/forschung/`

`mannheimer-innovationspanel-innovationsaktivitaeten-der-deutschen-wirtschaft`.

The CIS is a biennial survey of firms in the manufacturing and service sectors, designed to monitor innovation activity across EU member states. For Germany, the survey is representative at the two-digit industry level and includes both SMEs and large firms. It does not track firms longitudinally, making it a repeated cross-section. We focus on the three survey waves that include questions on environmentally beneficial innovations: 2009, 2015, and 2021.

The dataset provides detailed information on innovation outputs, types of environmental benefits targeted, and motivations for adopting green innovation. For our analysis, we retain firms that report introducing an innovation with environmental benefits in the past two years.

To examine the motivations behind green innovation, we use responses to the following survey question:

> "During [*the last two years*], how important were the following factors in driving your enterprise's decisions to introduce innovations with environmental benefits?"

Responses are recorded on a four-point scale: "high," "medium," "low," or "not important." We construct binary indicators equal to one if the firm rated a given factor as "low," "medium," or "high," and zero if it was "not important." This inclusive definition captures all cases where the firm viewed the factor as at least somewhat relevant to its innovation decision.

Table C.2 lists the variables and their corresponding survey items:

Table C.2: Variable Definition - Factors driving green innovation

Variable	Corresponding survey questions
Expected demand	*Current or expected market demand for environmental innovation*
Expected regulatory changes	*Environmental regulations or taxes expected in the future*
Existing regulations	*Existing environmental regulations* OR *Existing environmental taxes, charges or fees*
Reputation	*Improving your enterprise's reputation*
Voluntary standards	*Voluntary actions or standards for environmental good practice within your sector*
Government funding	*Government grants, subsidies etc. for environmental innovations*

C.3 Table of Green Goods for PRODCOM

Table C.3 gives the list of green goods we identify in PRODCOM (EUROSTAT 2025). The list is almost entirely based on Bontadini and Vona (2023), with a few minor additions. PRODCOM can be accesed on the EUROSTAT website: `https://ec.europa.eu/eurostat/web/prodcom/database`.

Table C.3: Green Good Table

	PRODCOM Number	Label
1	24107500	Railway material (of steel)
2	25112200	Iron or steel towers and lattice masts
3	25301150	Vapour generating boilers (including hybrid boilers) (excluding central heating hot water boilers capable of producing low pressure steam, watertube boilers)
4	25301230	Auxiliary plant for use with boilers of HS 8402 or 8403
5	25301330	Parts of vapour generating boilers and super-heater water boilers
6	25991131	Sanitary ware and parts of sanitary ware of iron or steel
7	25992910	Railway or tramway track fixtures and fittings and parts thereof
8	26112220	Semiconductor light emitting diodes (LEDs)
9	26112240	Photosensitive semiconductor devices; solar cells, photodiodes, phototransistors, etc.
10	26121330	Multiple-walled insulating units of glass
11	26511200	Theodolites and tachymetres (tachometers); other surveying, hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances
12	26511215	Electronic rangefinders, theodolites, tacheometers and photogrammetrical instruments and appliances
13	26511235	Electronic instruments and apparatus for meteorological, hydrological and geophysical purposes (excluding compasses)
14	26511239	Other electronic instruments, n.e.c.
15	26511270	Surveying (including photogrammetrical surveying), hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances (excluding levels and compasses), non-electronic; rangefinders, non-electronic
16	26511280	Non electronic surveying (including photogrammatrical surveying), hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances (excluding rangefinders, levels and compasses),
17	26514100	Instruments and apparatus for measuring or detecting ionising radiations
18	26514200	Cathode-ray oscilloscopes and cathode-ray oscillographs
19	26514300	Instruments for measuring electrical quantities without a recording device
20	26514310	Multimeters without recording device
21	26514330	Electronic instruments and apparatus for measuring or checking voltage, current, resistance or electrical power, without recording device (excluding multimeters, and oscilloscopes and oscillographs)
22	26514355	Voltmeters without recording device
23	26514359	Non-electronic instruments and apparatus, for measuring or checking voltage, current, resistance or power, without a recording device (excluding multimeters, voltmeters)
24	26514530	Instruments and apparatus, with a recording device, for measuring or checking electric gains (excluding gas, liquid or electricity supply or production meters)
25	26514555	Electronic instruments and apparatus, without a recording device, for measuring or checking electric gains (excluding gas, liquid or electricity supply or production meters)
26	26514559	Non-electronic instruments and apparatus, without a recording device, for measuring or checking electrical gains (excluding multimeters, voltmeters)
27	26515110	Thermometers, liquid-filled, for direct reading, not combined with other instruments (excluding clinical or veterinary thermometers)
28	26515135	Electronic thermometers and pyrometers, not combined with other instruments (excluding liquid filled)
29	26515139	Thermometers, not combined with other instruments and not liquid filled, n.e.c.
30	26515235	Electronic flow meters (excluding supply meters, hydrometric paddlewheels)
31	26515239	Electronic instruments and apparatus for measuring or checking the level of liquids

	PRODCOM Number	Label
32	26515255	Non-electronic flow meters (excluding supply meters, hydrometric paddle-wheels)
33	26515313	Electronic gas or smoke analysers
34	26515319	Non-electronic gas or smoke analysers
35	26515330	Spectrometers, spectrophotometers... using optical radiations
36	26515350	Instruments and apparatus using optical radiations, n.e.c.
37	26515381	Electronic ph and rh meters, other apparatus for measuring conductivity and electrochemical quantities (including use laboratory/field environment, use process monitoring/control)
38	26516350	Liquid supply or production meters (including calibrated) (excluding pumps)
39	26516370	Electricity supply or production meters (including calibrated) (excluding voltmeters, ammeters, wattmeters and the like)
40	26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus
41	26516620	Test benches
42	26516650	Electronic instruments, appliances and machines for measuring or checking geometrical quantities (including comparators, coordinate measuring machines (CMMs))
43	26516683	Other instruments, appliances, for measuring or checking geometrical quantities
44	26517015	Electronic thermostats
45	26517019	Non-electronic thermostats
46	26518200	Parts and accessories for the goods of 26.51.12, 26.51.32, 26.51.33, 26.51.4 and 26.51.5; microtomes; parts n.e.c.
47	26518550	Parts and accessories for automatic regulating or controlling instruments and apparatus
48	26702450	Other instruments and apparatus using optical radiation (UV, visible, IR)
49	26702490	Exposure meters, stroboscopes, optical instruments, appliances and machines for inspecting semiconductor wafers or devices or for inspecting photomasks or reticles used in manufacturing semiconductor devices, profile projectors and other optical instruments, appliances and machines for measuring or checking
50	27108230	Steel; iron or cast iron rails excl. current-conducting; with parts of non-ferrous metal - screws; bolts; nuts; rivets and spikes used for fixing track construction materials; assembled track
51	27108250	Iron or steel sleepers (crossties); rolled fish-plates and sole plates and check-rails (excl. screws; bolts; nuts; rivets and spikes used for fixing track construction materials)
52	27109230	Railway material (of steel)
53	27123130	Numerical control panels with built-in automatic data-processing machine for a voltage <= 1 kV
54	27123150	Programmable memory controllers for a voltage <= 1 kV
55	27123170	Other bases for electric control, distribution of electricity, voltage > 1000 V
56	27356200	Railway or tramway materials of steel or iron; not hot rolled
57	27401250	Tungsten halogen filament lamps for motorcycles and motor vehicles (excluding ultraviolet and infrared lamps)
58	27401293	Tungsten halogen filament lamps, for a voltage > 100 V (excluding ultraviolet and infra-red lamps, for motorcycles and motor vehicles)
59	27401295	Tungsten halogen filament lamps for a voltage <= 100 V (excluding ultraviolet and infrared lamps, for motorcycles and motor vehicles)
60	27401510	Fluorescent hot cathode discharge lamps, with double ended cap (excluding ultraviolet lamps)
61	27401530	Fluorescent hot cathode discharge lamps (excluding ultraviolet lamps, with double ended cap)
62	27402200	Electric table, desk, bedside, or floor-standing lamps
63	27403090	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for filament lamps and tubular lamps, including lighting sets for Christmas trees
64	27403200	Lighting sets for Christmas trees
65	27403930	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for filament lamps and tubular fluorescent lamps

	PRODCOM Number	Label
66	27512190	Other electromechanical appliances
67	27512690	Other electric space heaters
68	27521400	Non-electric instantaneous or storage water heaters
69	28112130	Steam turbines and other vapour turbines (excluding for electricity generation)
70	28112150	Steam turbines for electricity generation
71	28112160	Steam turbines and other vapour turbines
72	28112200	Iron or steel towers and lattice masts
73	28112400	Generating sets, wind-powered
74	28113100	Parts for steam turbines and other vapour turbines
75	28113200	Parts for hydraulic turbines and water wheels (including regulators)
76	28251130	Heat exchange units
77	28251380	Heat pumps other than air conditioning machines of HS 8415
78	28251410	Machinery and apparatus for filtering or purifying air (excluding intake filters for internal combustion engines)
79	28251420	Machinery and apparatus for filtering or purifying gases by a liquid process (excluding intake air filters for internal combustion engines, machinery and apparatus for filtering or purifying air)
80	28251430	Machinery and apparatus for filtering and purifying gases (other than air and excl. those which operate using a catalytic process, and isotope separators)
81	28251440	Machinery and apparatus for filtering or purifying gases by catalytic process (excluding intake air filters for internal combustion engines, machinery and apparatus for filtering or purifying air)
82	28251450	Machinery and apparatus for filtering and purifying gases with stainless steel housing, and with inlet and outlet tube bores with inside diameters not exceeding 1,3 cm (excluding intake filters for internal combustion engines)
83	28251470	Machinery and apparatus for filtering or purifying gases including for filtering dust from gases (excluding air filters for internal combustion engines, using liquid or catalytic process)
84	28291100	Producer gas or water gas generators; acetylene gas generators and the like; distilling or rectifying plant
85	28291230	Machinery and apparatus for filtering or purifying water
86	28291270	Machinery and apparatus for solid-liquid separation/ purification excluding for water and beverages, centrifuges and centrifugal dryers, oil/petrol filters for internal combustion engines
87	28298250	Parts for filtering and purifying machinery and apparatus, for liquids or gases (excluding for centrifuges and centrifugal dryers)
88	28301150	Vapour generating boilers (including hybrid boilers) (excluding central heating hot water boilers capable of producing low pressure steam, watertube boilers)
89	28301230	Auxiliary plan for use with boilers of 84.02 or 84.03, used
90	28301330	Parts of vapour generating boilers and super-heater water boilers
91	28992020	Machines and apparatus used solely or principally for the manufacture of semiconductor boules or wafers
92	28992060	Machines and apparatus used solely or principally for the manufacture of flat panel displays
93	28993945	Machines and apparatus used solely or principally for a) the manufacture or repair of masks and reticles, b) assembling semiconductor devices or electronic integrated circuits, and c) lifting, handling, loading or unloading of boules, wafers, semiconductor devices, electronic integrated circuits and flat panel displays
94	29102400	Other motor vehicles for the transport of persons (excluding vehicles for transporting >=10 persons, snowmobiles, golf cars and similar vehicles)
95	29102410	Motor vehicles, with both spark-ignition or compression-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion, other than those capable of being charged by plugging to external source of electric power
96	29102430	Motor vehicles, with both spark-ignition or compression-ignition internal combustion reciprocating piston engine and electric motor as motors for propulsion, capable of being charged by plugging to external source of electric power
97	29102450	Motor vehicles, with only electric motor for propulsion

	PRODCOM Number	Label
98	29102490	Other motor vehicles for the transport of persons (excluding vehicles with only electric motor for propulsion , vehicles for transporting > 10 persons, snowmobiles, golf cars and similar vehicles)
99	29105200	Motor vehicles specially designed for travelling on snow, golf cars and similar vehicles
100	29112130	Steam turbines and other vapour turbines (excl. for electricity generation)
101	29112150	Steam turbines for generation of electricity
102	29112200	Hydraulic turbines and water wheels
103	29113100	Parts for steam turbines and other vapour turbines
104	29113200	Parts of hydraulic turbines; water wheels incl. regulators
105	29231375	Absorption heat pumps
106	29231380	Heat pumps other than air conditioning machines of HS 8415
107	29231410	Machinery and apparatus for filtering or purifying air
108	29231420	Machinery and apparatus for filtering or purifying gases by a liquid process excl. intake air filters for internal combustion engines; machinery and apparatus for filtering or purifying air
109	29231430	Machinery filtering or purifying gases; by electrostatic process
110	29231440	Machinery and apparatus for filtering/purifying gases by catalytic process excluding intake air filters for internal combustion engines, machinery and apparatus for filtering/purifying air
111	29231450	Machinery filtering or purifying gases; by thermic process
112	29231460	Machinery filtering or purifying gases; other
113	29231470	Machinery filtering or purifying gases
114	29241130	Producer gas or water gas generators, acetylene and similar water process gas generators
115	29241150	Distilling or rectifying plant
116	29241230	Machinery and apparatus for filtering/ purifying water
117	29241270	Machinery and apparatus for filtering/ purifying liquids; for chemical industry
118	29245250	Parts for filtering and purifying machinery and apparatus, for liquids or gases (excluding for centrifuges and centrifugal dryers)
119	29562582	Machines and apparatus used solely or principally for the manufacture of semiconductor boules or wafers
120	29562586	Machines and apparatus used solely or principally for the manufacture of flat panel displays
121	29562588	Machines and apparatus used solely or principally for a) the manufacture or repair of masks and reticles, b) assembling semiconductor devices or electronic integrated circuits, and c) lifting, handling, loading or unloading of boules, wafers, semiconductors.
122	29721400	Instantaneuous water heater apparatus non-electric
123	30201100	Rail locomotives powered from an external source of electricity
124	30201200	Diesel-electric locomotives
125	30201300	Other rail locomotives; locomotive tenders
126	30202000	Self-propelled railway or tramway coaches, vans and trucks, except maintenance or service vehicles
127	30203100	Railway or tramway maintenance or service vehicles (including workshops, cranes, ballast tampers, track-liners, testing coaches and track inspection vehicles)
128	30203200	Rail/tramway passenger coaches; luggage vans, post office coaches and other special purpose rail/tramway coaches excluding rail/tramway maintenance/service vehicles, self-propelled
129	30203300	Railway or tramway goods vans and wagons, not self-propelled
130	30204030	Parts of locomotives or rolling stock
131	30921000	Bicycles and other cycles (incl. delivery tricycles), non-motorized
132	30921030	Non-motorized bicycles and other cycles, without ball bearings (including delivery tricycles)
133	30921050	Non-motorized bicycles and other cycles with ball bearings (including delivery tricycles)
134	30923010	Frames and forks, for bicycles
135	30923030	Parts of frames, front forks, brakes, coaster braking hubs, hub brakes, pedals crank-gear and free-wheel sprocket-wheels for bicycles, other non-motorized cycles and sidecars

	PRODCOM Number	Label
136	30923060	Parts and accessories of bicycles and other cycles, not motorised (excl. frames and front forks).
137	30923090	Other parts and accessories of bicycles and other cycles, not motorised
138	31203150	Programmable memory controllers; voltage <= 1000 V
139	31203170	Meter mounting boards and installation panels; voltage <= 1000 V
140	31501230	Tungsten halogen filament lamps (excl. ultra-violet; infra-red): for projectors
141	31501250	Tungsten halogen filament lamps for motorcycles and motor vehicles (excl. ultraviolet and infrared lamps)
142	31501293	Tungsten halogen filament lamps; for a voltage > 100 V (excl. ultraviolet and infra-red lamps; for motorcycles and motor vehicles)
143	31501295	Other tungsten halogen lamps; <= 100 V
144	31501510	Fluorescent hot cathode discharge lamps, with double ended cap (excluding ultraviolet lamps)
145	31501530	Fluorescent hot cathode discharge lamps (excl. ultraviolet lamps, with double ended cap)
146	31502200	Electric table; desk; bedside or floor-standing lamps
147	31503430	Electric lamps and lighting fittings, of plastic and other materials, of a kind used for filament lamps and tubular fluorescent lamps
148	32105235	Semiconductor light emitting diodes (LEDs)
149	32105237	Photosensitive semiconductor devices; solar cells, photodiodes, phototransistors, etc.
150	33201215	Electronic surveying & hydrographic instr.& appliances (incl. rangefinders; levels; theodolites & tacheometers; photogrammetrical instr.& appliances; excl. compasses)
151	33201219	Non-electronic surveying, hydrographic instr. and appliances (including rangefinders, levels, theodolites and tacheometers, photogrammetrical instr. and appliances; excluding compasses)
152	33201235	Electronic instruments and apparatus for meteorological, hydrological and geophysical purposes (excl. compasses)
153	33201253	Instruments and appliances used in geodesy; topography; surveying...
154	33201255	Non-electronic meteorological; hydrological and geophysical instruments and apparatus (excl. compasses)
155	33201257	Non-electronic surveying, hydro-, oceanographic instr./appliances (excluding rangefinders, levels, theodolites, tacheometers, photogrammetrical instr./app., compasses)
156	33203900	Installation of other special-purpose machinery n.e.c.
157	33204100	Installation of medical and surgical equipment
158	33204200	Cathode-ray oscilloscopes and cathode-ray oscillographs
159	33204330	Instruments and apparatus, for measuring or checking voltage: electronic
160	33204355	Voltmeters
161	33204359	Instruments and apparatus; for measuring or checking voltage: others
162	33205119	Other thermometers, not with other instruments, liquid, for direct reading
163	33205135	Thermometers; not combined with other instruments and not liquid filled; electronic
164	33205139	Thermometers, not combined with other instruments and not liquid filled, n.e.c.
165	33205313	Electronic gas or smoke analysers
166	33205319	Non-electronic gas or smoke analysers
167	33205330	Spectrometers, spectrophotometers using optical radiations
168	33205340	Exposure meters
169	33205350	Instruments and apparatus using optical radiations; n.e.c.
170	33205381	Electronic ph & rh meters; other apparatus for measuring conductivity & electrochemical quantities (incl. use laboratory/field environment; use process monitoring/control)
171	33205385	Viscometers, porosimeters and expansion meters
172	33205389	Other instruments and apparatus for physical and chemical analysis
173	33206350	Liquid supply or production meters (incl. calibrated) (excl. pumps)
174	33206370	Electricity supply or production meters (incl. calibrated) (excl. voltmeters; ammeters; wattmeters and the like)
175	33206550	Electronic instruments...measuring; checking geometrical quantities: 3 D

	PRODCOM Number	Label
176	33206583	Other instruments, appliances, for measuring or checking geometrical quantities
177	33206589	Other instruments; appliances and machines for measuring or checking
178	33207015	Electronic thermostats
179	33207019	Non-electronic thermostats
180	33207050	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus
181	33208120	Parts and accessories for surveying, geodesy, topography, levelling, photogrammetrical, hydro-, oceanographic, hydro-, meteorological, geophysical instruments excl. compasses
182	33208143	Parts and accessories for hydrometers and similar floating instruments, thermometers, pyrometers, barometers, hygrometers and psychrometers, recording or not, and any combination of these instruments
183	33208145	Parts and accessories of instruments and apparatus for measuring or checking the variables of liquids or gases (excl. for supply or production meters)
184	33208147	Microtomes, and parts and accessories
185	33209100	Installation of instruments and apparatus for measuring; checking; testing; navigating and other purposes
186	34102430	Vehicles with an electric motor, for the transport of persons (excl. vehicles for transporting >= 10 persons, snowmobiles, golf cars and similar vehicles)
187	34102490	Other motor vehicles for carrying people (excluding vehicles for transporting >= 10 persons, snowmobiles, golf cars and similar vehicles, electrically powered)
188	34105300	Vehicles for travelling on snow; golf cars; etc; with engines
189	35201100	Rail locomotives powered from an external source of electricity
190	35201200	Diesel-electric locomotives; =< 1000 kW power continuous rating
191	35201330	Rail locomotives powered by electric accumulators
192	35201390	Rail locomotives and locomotive tenders (excl. locomotives powered from an external source of electricity, locomotives powered by electric accumulators, diesel-electric locomotives)
193	35202030	Self-propelled railway coaches... powered by external electricity
194	35202090	Self-propelled railway or tramway coaches; vans and trucks; (diesel)
195	35203100	Railway or tramway maintenance or service vehicles (including workshops, cranes, ballast tampers, track-liners, testing coaches and track inspection vehicles)
196	35203200	Railway passenger coaches for speed =< 250 km/h; local
197	35203330	Tank wagons and the like; not self-propelled
198	35203350	Rail-or tramway goods vans & wagons; not self-propelled (incl. self-discharging and open vans & wagons) with non-removable sides; height > 60 cm; & other wagons
199	35204030	Parts of locomotives or rolling stock
200	35204055	Railway or tramway track fixtures and fittings, and mechanical or electromechanical signalling, safety or traffic control equipment
201	35204058	Parts of railway or tramway track fixtures and fittings; and for electromechanical signalling; safety or traffic control equipment
202	35204059	Mechanical (and electromechanical) signalling; safety or traffic control equipement (excluding equipment and material for track)
203	35421030	Bicycles and other cycles; not motorized; without ball bearings
204	35421050	Mountain bike
205	35422013	Frames for bicycles, other non-motorized cycles and sidecars (excluding parts of frames)
206	35422015	Front forks for bicycles; other non-motorized cycles and sidecars (excl. parts of front forks)
207	35422019	parts of cycles
208	35422023	Wheel rims for bicycles other non-motorized cycles and sidecars
209	35422025	Wheel spokes for bicycles; other non-motorized cycles and sidecars
210	35422027	Hubs without free-wheel or braking device for bicycles, other non-motorized cycles and sidecars
211	35422033	Coaster braking hubs and hub brakes

	PRODCOM Number	Label
212	35422039	Brakes for bicycles and other non-motorized cycles (excl. coaster braking hubs and hub brakes)
213	35422040	Saddles for bicycles and other non-motorized cycles
214	35422053	Pedals
215	35422055	Crank-gear
216	35422063	Handlebars
217	35422065	Luggage-carriers for bicycles and other non-motorized cycles
218	35422067	Derailleur gears for bicycles and other non-motorized cycles
219	35431200	Parts and accessories of invalid carriages
220	40301003	Heat - heating plants (heat produced by heating plants using fossil fuels; biomass or waste; sold to third parties)
221	40301005	Heat - geothermal (heat produced in geothermal fields; sold to third parties)
222	23121330	Multiple-walled insulating units of glass
226	28112160	Steam turbines and other vapour turbines (excl. for electricity generation)
227	28112200	Hydraulic turbines and water wheels
229	28113200	Parts of hydraulic turbines; water wheels incl. regulators
231	28251410	Machinery and apparatus for filtering or purifying air
232	28251441	Machinery and apparatus for filtering/purifying gases by catalytic process excluding intake air filters for internal combustion engines, machinery and apparatus for filtering/purifying air
233	28291100	Distilling or rectifying plant
234	28298251	Parts for filtering and purifying machinery and apparatus, for liquids or gases (excluding for centrifuges and centrifugal dryers)
237	27123150	Programmable memory controllers; voltage <= 1000 V
240	26516370	Voltmeters
244	26702490	Exposure meters
248	26515175	Parts and accessories for hydrometers and similar floating instruments, thermometers, pyrometers, barometers, hygrometers and psychrometers, recording or not, and any combination of these instruments
250	30201200	Diesel-electric locomotives; =< 1000 kW power continuous rating
251	30203100	Self-propelled railway or tramway coaches; vans and trucks; (diesel)
252	30921000	Bicycles and other cycles (including delivery tricycles), non-motorised
253	30923060	Bicycles and other cycles, not motorised, with ball bearings.
254	30923010	Frames for bicycles, other non-motorized cycles and sidecars (excluding parts of frames)
255	22111200	Wheel rims for bicycles other non-motorized cycles and sidecars