Inventors' Personal Experience of Natural Disasters and Green Innovation*

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Abstract

In this article, we show how inventors' personal experiences of natural disasters lead to increased green innovation. Exposed inventors change their expectations about the profitability of their innovation activities. They expect heightened demand for green goods and more stringent environmental regulation. We match patent records of French and German inventors to detailed information on natural disasters. This allows us to exploit exogenous variation in inventors' exposure to natural disasters. In affected areas, exposure results in, on average, an 8% increase in green patents. The effect is primarily driven by increased innovation in mitigation technologies that reduce emissions. We find striking patterns of declining disaster salience over time and no effect on non-green innovation. By linking an inventor survey with our natural disaster measure, we provide novel causal evidence on how large shocks change inventors' higher-order beliefs about the preferences of others. We do not find significant spatial spillovers, underlining the importance of personal experiences. In line with our model, effects are significantly larger in product markets with fiercer competition and when inventors can build on the shoulders of giants.

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1 Introduction

What drives inventors to pursue new ideas? A large body of literature has investigated how financial incentives play a key role to spur on innovation. Key factors, such as the competitive environment (Aghion and Howitt 1992; Aghion et al. 2005) and product market size (Acemoglu 2002; Acemoglu and Linn 2004), influence inventive activity. Additionally, the inventor's personal experiences and social background are important in determining the direction of their research efforts (Feng et al. 2021). For instance, children's exposure to specific technology fields can affect the trajectory of their innovation careers. (Bell et al. 2019).

At the onset of any innovation, uncertainty remains in regard to market conditions and future profitability. Therefore, understanding what drives expectations about market conditions and future profitability is crucial. Here, individual personal experiences can affect inventors' set of information and shape their expectations. An idea, going back to early work by Hayek: "practically every individual has some advantage over all others in that he possesses unique information of which beneficial use might be made" (Hayek 1945, p. 521).

In this article, we explore how inventors' personal experiences of natural disasters shape their innovation choices. In particular, our research aims to shed light on inventors' choices regarding green innovation—crucial technologies in the fight against climate change (see, for instance, Acemoglu et al. 2012; Acemoglu et al. 2016). To study this question, we exploit random variation in inventors' personal experience of natural disasters. Local disasters heighten climate change salience (Djourelova et al. 2024) and shift consumption toward green products (Chae et al. 2025).

Using patent data, we show a drastic increase in green innovation in affected areas. This effect is particularly strong for mitigation technologies, precisely those technologies aimed at reducing the root cause of climate change -GHG emissions. Effects are local, with a lack of significant spillovers, highlighting the role of being personally affected. Additionally, we merge our natural disaster data with a survey on inventive firms. We find that inventors update their expectations about the pecuniary rewards of their innovation effort. Natural disaster exposure change inventors' higher-order beliefs about the preferences of consumers and voters. They expect stronger consumer demand for green goods and stricter environmental regulation. Furthermore, we show that competitive markets, market size in the spirit of the directed technical change literature, and environmentally conscious consumers are crucial to ensuring that inventors respond to new information.

We contribute to the innovation literature by introducing a new mechanism that formalizes how inventors' personal experiences directly influence their profitability expectations. Additionally, we expand the analysis of how natural disasters affect innovation onto patents. Here, our main contribution is to show a marked increase in the innovation of mitigation technologies - a fact previously undocumented in the literature. We additionally contribute to the literature on belief formation. Understanding why individuals adjust their higher-order beliefs—beliefs about the preferences of others—and how these beliefs translate into economic decision-making remains a significant gap in the literature (Coibion et al. 2021). Much of the evidence comes from experiments or information treatments in surveys. Our setting allows us to contribute to this literature by observing how large shocks affect higher-order beliefs in a high-stakes environment.

Our analysis proceeds in three steps: we first estimate the impact of natural disaster exposure on green patenting using event-study designs that levage random variation in disaster exposure. Second, our theoretical model discusses how these disasters affect local inventors' profitability expectations. We also test the wider implications of our model empirically. Third, by linking firm-level survey data to our natural disaster measure, we provide causal evidence for how higher-order beliefs change due to natural disaster exposure.

Using patent data from 1994–2014 and the location of German and French inventors from De Rassenfosse et al. (2019), we spatially match inventors and natural disasters.[1] We use data from the Emergency Events Database (Guha-Sapir et al. 2022), complemented with geolocations from the Geocoded Disasters dataset (Rosvold and Buhaug 2021). We exploit a patent classification that identifies a patent as green if its technical content pertains to mitigation or adaptation against climate change. Our match is done on the region level, to which we aggregate all patents and natural disasters. These regions correspond to the arrondissement level in France and to the Kreis level in Germany. We account for multiple and geographically dispersed inventors by weighing each patent with the share of its inventors living in a particular region. Additionally, we control for technology trends for every region-year pair and include region and country-year fixed effects.

We find that, on average, one additional natural disaster increases green patenting by 8.2% relative to the sample average.[2] However, this impact evolves dynamically over time. Notably, five years after the disaster, the number of green patents rises by 25%, with the effect gradually tapering off thereafter. A 25% increase corresponds to 0.64 additional green patents in the exposed region. For comparison, there are on average 2.54 new green patents per region per year. There are no spillovers from natural disasters more than 50 km away, and only minor spillovers from natural disasters in directly adjacent regions. The effect is local and deeply linked to the personal experience of the inventor. We find no effect on non-green patents. Our results are robust when using the alternative estimator of Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024).

We document a novel fact. Innovation responses are particularly pronounced for

[1]We use patent data from the European Patent Office's PATSTAT database. For further information on PATSTAT, see section 2.

[2]This effect is calculated by normalizing the outcome variable against its sample average across all years and regions. For details, see equation (3).

mitigation technologies, which aim to reduce greenhouse gas (GHG) emissions across various sectors, including electricity generation, goods production, and transportation. On average, patents for these technologies increase by approximately 8.4%. The effects on mitigation technologies are stronger than on adaptation technologies, such as those aimed at protection against harsher weather or flood damage. Mitigation technologies are not disaster-specific. Thus, heightened climate change salience drives an innovation response beyond immediate local threats. In terms of magnitude, our estimate is similar to the effect that the EU-ETS had on the patenting activity of affected firms (Calel and Dechezleprêtre 2016). Related studies also discuss how green innovation responded to the oil crisis of the 1970s (3% increase, see Popp 2002; Hassler et al. 2012). Using more contemporary data, Aghion et al. (2016) find a 10% increase in green innovation due to 10% higher fuel prices.

But how exactly does this large local impact on inventive activity materialize? Formally, we propose a new mechanism that goes through inventors' higher-order beliefs and profit expectations. We do so by adapting and extending the theoretical work in Aghion et al. (2023). Consumers have preferences over the consumption value of a good and its carbon footprint. Put differently, consumers care about a good, e.g., "transportation to destination A," and the emissions of their chosen mode of transportation.

Into this framework, we introduce local inventors, who have expectations about the profitability of green goods. These expectations are driven by anticipating individuals to be more environmentally conscious. On the one hand, more environmentally conscious consumers directly demand more green goods. On top of that, they also express their preferences politically by demanding more stringent environmental regulation, which also benefits green products. Local inventors' expectations are affected by their personal experiences, i.e., through natural disaster exposure. In turn, these expectations determine an inventor's innovation decision.

To corroborate our mechanism, we link firm-level survey data from the German part of the Community Innovation Survey to our natural disaster data. Our findings show that natural disasters influence inventors' higher-order beliefs. After such events, they anticipate higher demand for green goods and expect stricter environmental regulation in the future. This in turn raises their expectations about the profitability of green innovation.

In our model, competition exacerbates the effect higher expectations have on green innovation. An inventor in a competitive industry is more inclined to innovate, as green innovation differentiates her product from her competitors' products. We can thus derive an empirically testable hypothesis which states that inventors in competitive industries react more strongly to natural disaster exposure. To test this hypothesis, we match our patent data with data on industry competition. In line with out hypothesis, inventors facing a high degree of competition, as measured by inverse profit margins, respond significantly more to natural disaster exposure than those in non-competitive markets. This finding underscores that pecuniary economic incentives—rather than purely intrinsic motivations or environmental concerns—play a central role in driving innovation responses.

In line with earlier literature on market size and the direction of innovation (Acemoglu et al. 2012; Acemoglu et al. 2016), we find stronger effects in product markets with larger green good shares. These findings are in spirit of the "building on the shoulders of giants" feature of directed technical change. We proxy for green good demand as the share of green goods in a product market, using data from PRODCOM and a list of green products from Bontadini and Vona (2023).[3]

An important implication of our work is that a well-functioning market for green innovations is crucial to ensure that inventors translate new information about climate change into increased innovation output. Additionally, our findings point toward an inefficiency in how innovation responds to natural disasters. Purely local responses yield higher research costs for the same amount of innovation than a global response would.

However, local responses to natural disasters still have global economic effects, as our results remain robust for "triadic" patents. These are patents filed across the globe at the three most important patent offices (see Dernis and Khan 2004; Rassenfosse and Pottelsberghe de la Potterie 2009). Our results also hold when only considering high-value patents as measured by patent citations (Trajtenberg 1990).

Lastly, we rule out government research funding as an alternative mechanism. By matching French data on research grants to our sample regions, we show that there is neither a significant uptick in the number of research grants nor in the amount granted to affected areas post-natural disaster.[4] Additionally, we show that natural disaster exposure has no impact on German innovators' likelihood of reporting government funding support.

Our work contributes to the literature on the driving forces of innovation, the literature on how personal experience matters for economic expectations and higher-order beliefs, and the literature on how natural disasters affect economic development.

We contribute to the innovation literature by introducing a new mechanism that formalizes how inventors' personal experiences directly influence their profitability expectations. Innovation thus not only depends on the market conditions for green goods (such as in Aghion et al. 2023), but also on the expectations thereof.

Our work expands the literature on personal experience as a determinant of expectations and economic behavior to a new domain. This literature has for the most part focused on expectations about macroeconomic conditions, such as inflation (Malmendier and Nagel 2016), severity of recessions (Malmendier and Nagel 2011), house

[3] For PRODCOM see: `https://ec.europa.eu/eurostat/web/prodcom`

[4] Importantly, this is not to say that the government does not respond with other means of disaster relief (e.g., reconstruction of destroyed infrastructure).

prices (Kuchler and Zafar 2019), and stock market returns (Laudenbach et al. 2023). This literature and some notable exceptions are summarized by Giuliano and Spilimbergo (2024). Perhaps most closely related is work by Gallagher (2014), who shows that flood insurance take-up drastically increases after local floods but declines quickly with fading disaster salience.

With our survey results, we contribute to the literature that has researched how higher-order expectations are formed (Coibion et al. 2021). We show that affected inventors expect heightened environmental preferences of those around them. They not only expect these preferences to materialize in more green good demand, but also in more pro-environmental political choices, which lead to more stringent environmental regulation. In terms of the outcome, our survey results are perhaps most closely related to Horbach and Rammer (2025), who show that self-reported climate affectedness makes it more likely for firms to engage in green innovation.

Inventor responses are focused on green innovation, which points to a salient link between natural disasters and environmental consciousness. Moreover, our results point to an overreaction of those with the most salient experience of the natural disaster. These findings link to the recent literature on salience (Bordalo et al. 2022b) and overreaction of macroeconomic expectations (Bordalo et al. 2022a). Related to climate change, Djourelova et al. (2024) show that natural disasters make climate change issues more salient, but that this effect declines over time. Further, they show that natural disaster exposure leads to changes in environmental beliefs, which in turn are positively correlated with real world pro-environmental decisions. There is also work on how consumer demand is becoming more green in disaster prone regions (Chae et al. 2025).

To our knowledge, we are the first to show that natural disasters have an effect on mitigation technologies. We thus expand the scope of analysis onto patents for technologies that not only adapt to the adverse effects of climate change but also combat its root cause: greenhouse gas emissions. Mitigation technologies are a significantly larger part of overall green technologies than adaptation technologies. In terms of magnitude, the uptick in mitigation technologies is larger than the effect on adaptation technologies. The literature that studies the effects of climate change on innovation has so far focused predominantly on adaptation technologies, which aim to shield humans from the adverse effects of climate change. Miao and Popp (2014) show in a cross-country study that floods, droughts, and earthquakes induce more innovation in technologies that directly deal with the adverse effects of these disasters.[5] In a similar vein, Moscona (2021) and Moscona and Sastry (2023) show that droughts and extreme temperature events lead to an increase in agricultural technologies resistant to these changing conditions. In their model, green innovation mainly reduces incurred environmental damage for the producer. In our work, benefits are driven by increased valuation of green products as a whole. Further, we expand the scope of analysis onto a more general set of

[5] An example given by Miao and Popp (2014) is an increase in patents that pertain to developing crops that are more resistant to prolonged periods of drought.

technologies.

More generally, we contribute to the literature that discusses the economic and behavioral impact of natural disasters. While natural disasters certainly have strong adverse effects on economic development and affected individuals (e.g. Boustan et al. 2012; Hsiang et al. 2017), our results contribute to a small part of the literature that highlights positive effects of natural disaster exposure. In our work, we show that natural disasters carry information and thus act as a stimulant to economic growth. This relates to earlier work which put forward the idea that disasters, through their destruction, force a more efficient outcome, e.g., Hornbeck and Keniston (2017) on faster urban growth, or Deryugina et al. (2018) and Nakamura et al. (2022) on more efficient labor market sorting through post-disaster relocation.

Our findings have two important policy implications. Efficient markets for green innovation are key to ensure that inventors respond to new information about climate change. Second, the local character of how information shocks, such as natural disasters, are internalized by the inventor leads to a sub-optimal level of aggregate innovation output. We show that a policymaker can improve on the status quo by equalizing information across locations, namely, propagating the information to unaffected regions. Depending on the cost of such information campaigns, this is perhaps a more cost-effective method of incentivizing green innovation than providing subsidies to inventors.

The rest of this article is organized as follows. Section 2 describes our data. Section 3 describes our empirical approach. Section 4 presents our results. Section 5 starts with our theoretical model and outlines our proposed mechanism. We additionally show corroborating survey evidence, and provide evidence for changes in higher-order beliefs. Section 6 discusses additional results on patent value, inventor heterogeneity, and the general robustness of our results, and section 7 concludes.

2 Data

2.1 Patents

The starting point of our dataset is the European Patent Office's (EPO) PATSTAT. For our purposes, it contains almost all patent applications from inventors living in France and Germany for our period of interest (1994–2014).

Crucially, this includes not only patents filed at the European Patent Office (EPO) but also those filed at the national patent offices of its member states. Moreover, PATSTAT encompasses data on patents filed at non-EPO jurisdictions. Given our focus on inventors residing in France and Germany—rather than solely on patents filed within these countries— it is essential to have access to patent records from offices beyond the EPO. For example, a French inventor, responding to a natural disaster, may choose to file a patent in the United States for strategic purposes, such as anticipating higher commercial value in that market. Our dataset enables us to still capture such cross-border patenting behavior.

PATSTAT thus also contains information about patents filed at the Tokkyochō—the Japanese Patent Office (JPO)—and the United States Patent and Trademark Office (USPTO), which together with the EPO encompass the most important patent offices worldwide. Inventions patented at each of the EPO (and its member states), the JPO, and the USPTO are sometimes called triadic patents, which in and of itself is a measure of a patent's value (see, for instance, Dernis and Khan 2004; Rassenfosse and Pottelsberghe de la Potterie 2009, Dechezleprêtre et al. 2017). We use this indicator to show that our results hold for the most valuable patents.

Importantly, PATSTAT contains information on the type of technology that is patented. We use the Cooperative Patent Classification (CPC), which contains an identifier for a patent being "green".[6] For this, we consider the Y02 classification and its underclasses. A "Y02" patent is any patent flagged as "technologies or applications for mitigation or adaptation against climate change." A green technology thus has to either combat/reduce the effect humans have on the environment or mitigate the adverse effect climate change has on human society. Figure 1 plots the patenting activity in our sampled countries from the year 1994–2014, split by patents being either green or non-green.

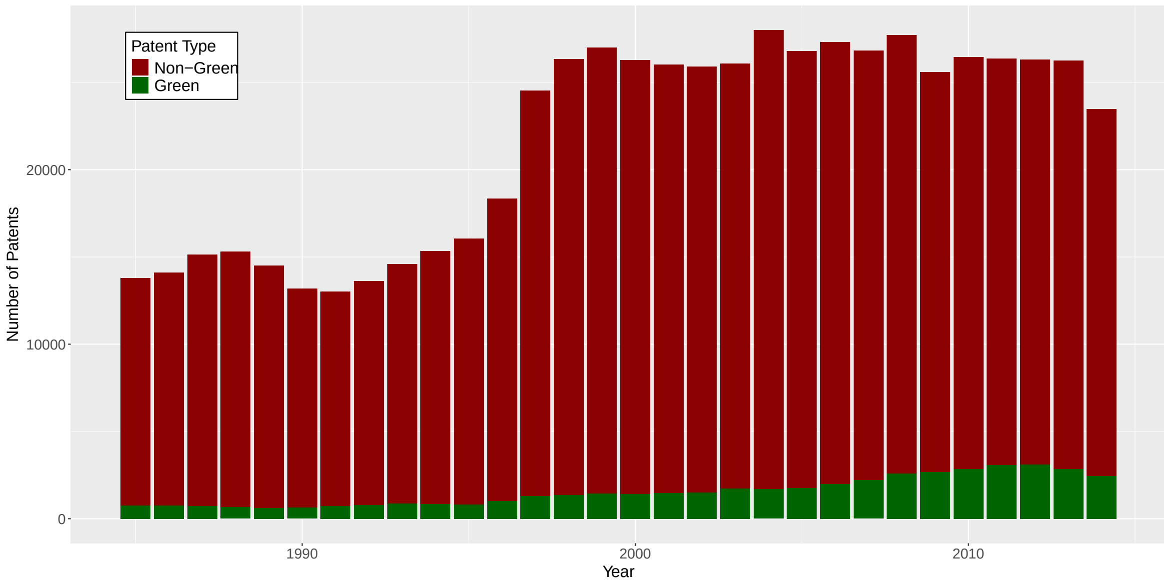

Figure 1: Patenting Activity in France and Germany over Time

Knowing the precise CPC class of a patent allows us to categorize patents into broad technological groups such as those related to, e.g., agriculture, concrete and cement making, or combustion engines. Using this information, we construct indicators for a region's share of patents within a given technology class.

[6]CPC is an extension of the more well-known International Patent Classification (IPC). IPC lacks a precise identifier for green patents.

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. According to the authors, this data roughly corresponds to city-level assignments, enabling us to link all patents in our sample to the location of their inventors. However, in most cases, we are unable to directly link an inventor's location to their name in PATSTAT. As a result, while we know the location of almost all inventors on a patent and the names of those inventors, we often cannot match individual names to specific locations.

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 "novelty of the art" - a 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) Guha-Sapir et al. (2022). EM-DAT contains information on 26000 natural and technological disasters from 1900 to the present. In our analysis, we are interested in the emergence of innovations to combat and mitigate the consequences of climate change. Accordingly, we only consider natural catastrophes that occur more frequently due to climate change. In this case, these are floods, storms, extreme temperature events, and droughts. The CRED includes a disaster in the database if it meets 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]

The emergency event database provides inaccurate and often missing information on the disaster location. Therefore, we complement the EM-DAT data with geolocations from the Geocodes Disaster dataset (GDIS) (Rosvold and Buhaug 2021). GDIS data extends the emergency event database with precise information on the location of

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

disasters between 1960 and 2018. The authors processed location information from EM-DAT with an automated script to match these locations to global administrative areas (GADM) version 3.6. The data matches disasters often at the first-order administrative area, but if possible, at the second- or third-order administrative level.

In our main analysis, our sample includes the two largest European patenting countries, France and Germany. We restrict our analysis to the period from 1984 to 2018. Information on past disasters in EM-DAT is available starting in 1900. However, the data are very patchy for the first decades. The data quality in EM-DAT improved for disasters after 1984. Information on the geolocation in GDIS is only available between 1960 and 2018. For our full sample, we end up with 163 distinct natural disasters that can happen in multiple regions at once.

2.3 Community Innovation Survey

We rely on the German part of the Community Innovation Survey (CIS) to obtain firm-level information on key determinants and alternative measures of green innovation. The CIS is a biennial European survey collecting information on firms' innovation activities. Questions on green innovations are asked every 6 years, so we use the data from the 2009, 2015, and 2021 waves. In total, our analysis is based on 18,425 observations.

We construct two distinct measures for green innovation: one for the introduction of green innovations within firms and the other for the introduction of new green products or services. The first measure captures internal green innovations that provide one or more of the following environmental benefits: reduction in energy, material, or water usage; decrease in CO2/air/water/soil pollution; replacement of fossil fuel energy sources with renewable energy sources; or substitution of materials with less hazardous alternatives. On average, 48.3% of firms reported the introduction of internal green innovations. The second measure indicates the introduction of green product or service innovations that offer one or more of the following environmental benefits: reduction of CO2/air/water/soil pollution; facilitation of product recycling after use; or extension of product lifespan through the development of longer-lasting products. In our data sample, on average, 34.8% of firms introduced new products or services with environmental benefits.

Additionally, firms were asked to indicate the importance of the following factors for their introduction of green innovations: existing environmental regulations, voluntary initiatives or standards for environmental best practices, anticipated future regulations, current or expected market demand, and government subsidies. The primary drivers of green innovations among the surveyed firms are existing environmental regulations, with 46.6% of firms identifying this factor as significant. Additionally, voluntary actions or standards for environmental best practices within their sector were noted as important by 45.6% of firms. Furthermore, anticipated future regulations or taxes motivated 43.5% of the firms, while current or expected market demand for environmental innovations influenced 39.3%. Lastly, 28.2% of firms cited government grants and subsidies as a key motivating factor.

2.4 Competition

Furthermore, we are interested in how market conditions play a role in inventors' responses to natural disaster exposure. To get at the effect of how the level of competition faced by the inventor affects their response to natural disasters, we use CompNet (2022) to obtain industry-by-country-by-year level data on competition. CompNet provides aggregated indicators of competition, along with other variables, by consolidating administrative data from all participating countries and offering these indicators at various levels of aggregation. This data is collected for all the countries in our analysis, starting at the earliest in the year 2000. For some countries in our sample, this information is only available for later years. See Table 14 in the appendix for an overview of the time spans available in the CompNet data for every country.

Given that our model focuses on profitability, we measure competition at the industry-year-country level using profit margins $margin_{ktc} = \frac{\text{Operating Profits}_{ktc}}{\text{Nominal Revenue}_{ktc}}$.

CompNet and PATSTAT use the European Classification of Economic Activities (NACE Rev 2) to classify industries, which allows us to link both datasets. For patents, we know which industry a patent belongs to, including a weight if it belongs to multiple industries. We link these datasets at the 2-digit level, as this is the most granular information in CompNet. See section 5.3.1 for our exact procedure and results.

2.5 Green Goods

We are interested in knowing how big the market for green inventions is in different industries. We proxy for the level of green good demand faced by inventors at the time of their invention, by calculating the share of products in that market being green. To do so, we use PRODCOM data and apply the methodology proposed in Bontadini and Vona (2023). PRODCOM, compiled by Eurostat, provides detailed information on manufacturing production values in Europe, covering 4,288 individual products. For our purposes, it spans the period from 1995 to 2014 for core European countries. The PRODCOM classification is embedded within the NACE industrial classification system, with each PRODCOM code consisting of eight digits, the first four of which align with NACE industry codes. This enables us to calculate industry-level averages. To identify green products, we rely on the list provided in Bontadini and Vona (2023). Since some PRODCOM product codes have changed since their publication, we adapt their list to include a few new codes[8]. The alignment of PRODCOM with NACE allows us to assign products to 4-digit (and 2-digit) industries, facilitating the calculation of

[8]See Section A.7.3 in the appendix for our list of green products.

each industry's share of green production. The aggregation at the NACE 4-digit level enables us to link the share of green products in an industry to the patent data.

2.6 French Research Funding

We gather information on research projects funded by public authorities in France from ScanR. This platform, created by the French Ministry of Higher Education, Research, and Innovation, enables us to identify French organizations involved in publicly funded research and innovation projects. In total, 121,451 publicly funded research projects starting from 1999 are listed in this database (Ministère de l'Enseignement supérieur 2023). Most research projects included in this dataset are funded by the European Union via (Horizon 2020/Horizon Europe, the Seventh Framework Programme for Research and Technological Development), the French National Research Agency (ANR), or the Hubert Curien Partnership (PHC) that provides funding for collaborative research projects with French researcher and their counterparts in other countries. [9]

3 Empirical Strategy

3.1 Data Sample

We merge our patent and natural disaster data spatially at the arrondissement level in France and the Kreis level in Germany, both of which roughly correspond to US counties.[10] Throughout the analysis, we refer to this level of observation as the "regional" level or simply "region," which should not be confused with a 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:

[9] We downloaded the data in December 2023; therefore, our dataset includes all funded research projects from 1999-2023.

[10] The arrondissement level corresponds to the third administrative level used in France, while the Kreis level corresponds to the second administrative level used in Germany. There are 403 Kreise and 350 arrondissement.

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

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:

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

and equivalently for non-green patents. We do the same when aggregating different subclasses, or when splitting the sample on e.g. competition.

To each of these regions we then merge our natural disaster data. 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. 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 French region "Occitanie," all 36 arrondissements within Occitanie are coded as being exposed during this period.

Figure 2 visualizes the resulting variation in green patenting and natural disaster exposure used in our analysis.

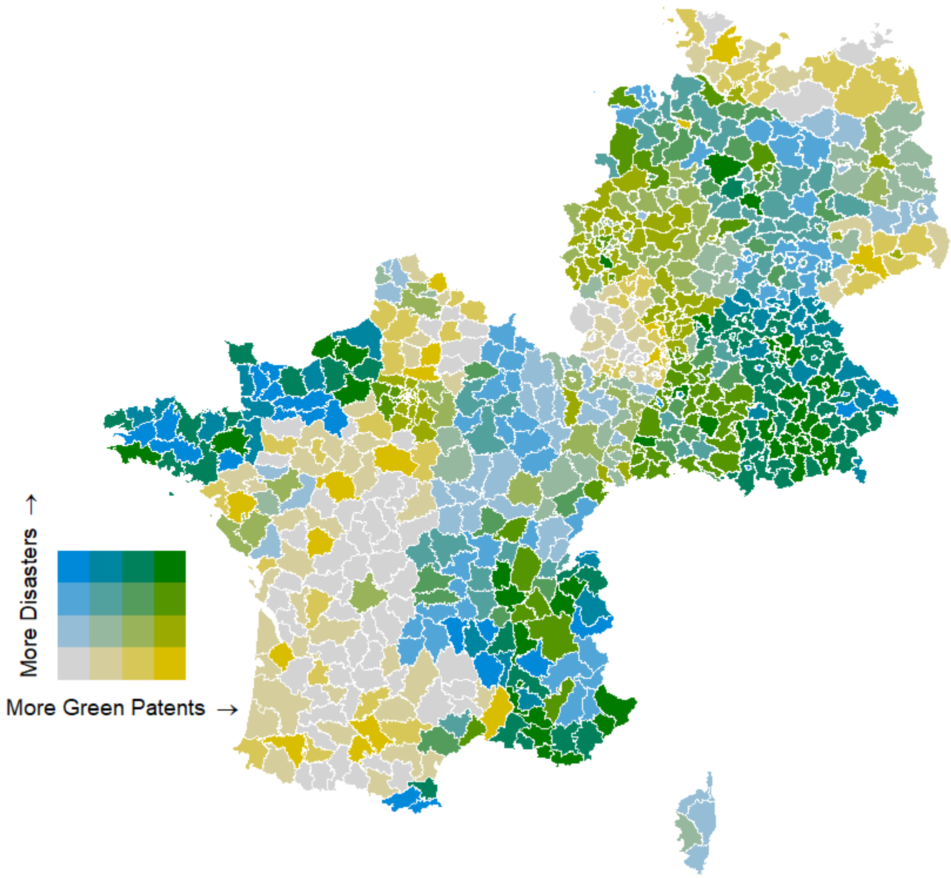

Figure 2: Bivariate Map of Green Patent and Disaster Counts

3.2 Estimation

The process of innovation inherently takes time, and the path to a final patent application is often lengthy. In the context of our analysis, experiencing a flood might prompt people to adopt more eco-friendly/energy efficient materials in constructing their houses. This, in turn, could lead local inventors to revise their expectations about the profitability of such products, incentivizing them to increase their R&D efforts in these areas. However, from the inception of a new idea to the final realization of a patentable prototype, several years may pass. To account for this, we consider it natural to use an event-study design, which allows us to observe the dynamics of patenting following a natural disaster. Our baseline specification, applied to the data, is presented in the equation:

$$P(\mathbf{Y02}_{lt}) = \sum_{s=-5, s\neq -1}^{11} \beta_s D^s_{l,t} + \gamma_1 CPC_{lt} + \gamma_2 \lambda_{ct} + \gamma_3 \lambda_l + \epsilon_{lt} \tag{4}$$

with

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

where $P(\mathbf{Y02}_{lt})$ is the normalized count of patents (as specified in equation (3)), and $T_{l,t-s}$ 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. CPC_{lt} is a vector of controls on a region's innovation composition at time t. For every region, we calculate the percentage of patents falling into a broad CPC class[11]. 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, that frequently patents, leaving a region, which would clearly affect patenting in class C - "Chemistry; Metallurgy". We include region λ_l and country-by-year λ_{ct} fixed effects. The region fixed effects absorb underlying region-specific natural disaster risk characteristics and account for differences, such as one region being more accustomed to floods than another. Furthermore, the region fixed effects implicitly control for regional time-invariant differences, such as institutional characteristics. The time-fixed effects account for a general increase in disaster risk over time. Our coefficient of interest, β_s, compares the patenting activity of regions that experienced a disaster at $t-s$ with that of regions that did not experience a disaster at the same point in time. We cluster standard errors at the regional level, i.e., the level of our identifying variation.

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 simplified difference-in-difference equation:

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

where $\sum_{s=0}^{\infty} T_{l,t-s}$ 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.

While our region fixed effects control for time-invariant differences in disaster risks, disaster risk might change differentially across regions with increasing climate change. Fortunately, natural disasters on the scale observed in our data are still quite infrequent events, making anticipation of such events difficult. Furthermore, these underlying risk

[11] 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).

characteristics are difficult to observe and, thus, unlikely to significantly affect inventor behavior.

In the case of floods, it is likely that not an entire region is flooded. Therefore, disaster exposure might vary within a region that we consider treated. Consequently, we estimate the average effect that disaster exposure has on both directly and potentially only indirectly affected inventors.

Furthermore, we only observe inventors at the time when they file a patent application. The underlying assumption of our paper is that inventors do not move between being exposed to a natural disaster and filing a patent. If inventors move out of affected regions, we would expect attenuation bias, whereas if inventors move into affected regions, we would overestimate the results. In our case, we argue that the first scenario is more likely; however, we are unable to directly verify this.

Our data only contains severe natural disasters. We would thus like to caution that not all exposure to the forces of nature induces changes in inventor behavior.

4 Main Results

Figure 3 presents our main results when estimating equation (4). Our data is aggregated on a yearly basis. Year 0 thus represents the partially treated year. For example, if region l experienced a natural disaster in June, only patents filed in the months after could potentially be influenced by the natural disaster. 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 but remaining positive 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. A strong initial impact on beliefs and expectations triggers an impulse to inventive activity, with the resulting innovations 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). As innovation takes time, the lack of an immediate uptick is unsurprising.

Interestingly, we do not observe a response in non-green innovation, indicating a lack of significant crowding out of inventive activity. Natural disasters spur additional green innovation without substantially altering a region's non-green innovation landscape.

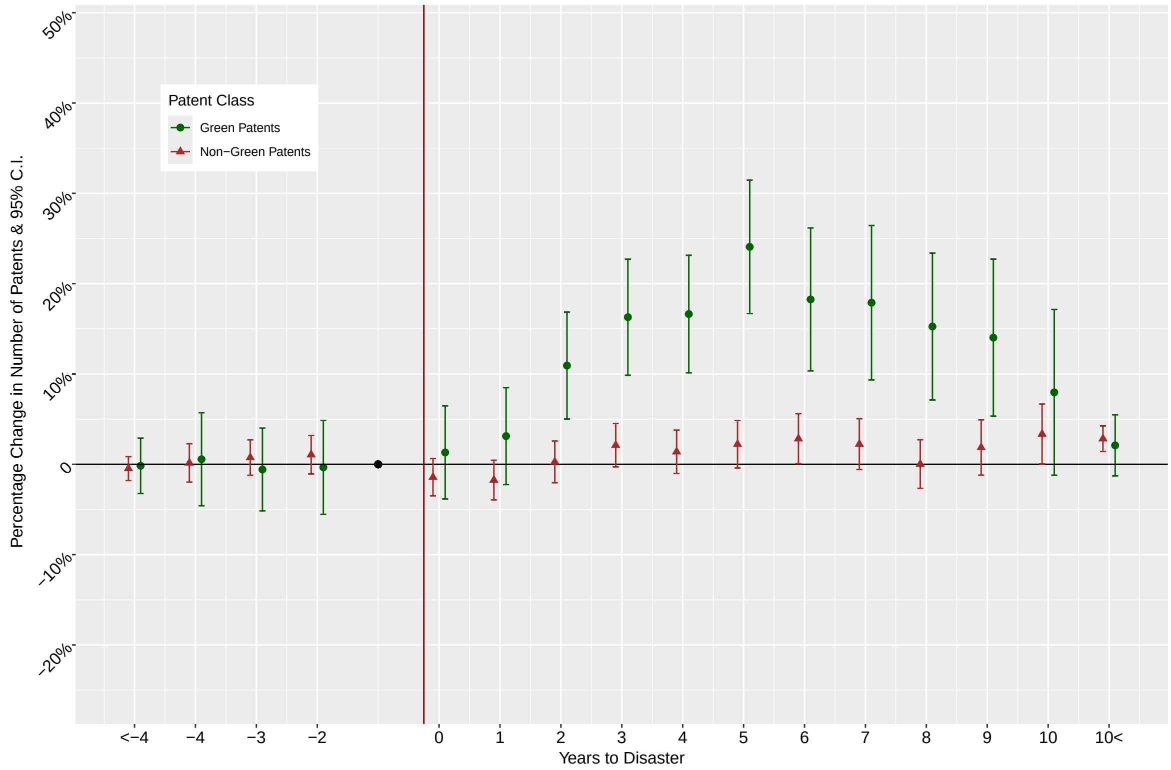

Figure 3: Patenting following the Exposure to a Natural Disaster

Note: This figure depicts the results for our baseline specification when using our pooled country sample (France and Germany). 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.

The overall magnitude of our findings is substantial. Calel and Dechezleprêtre (2016) report a 10% increase in green patents among firms affected by the EU-ETS in its early years. In comparison, we observe a larger spike in innovative activity five years after the disaster, while our long-run effect—approximately 8.2% relative to the sample average (see Table 1)—falls just short of their estimate. Natural disaster exposure leads to a large and significant response of local inventors.

The graphical representation of our event study supports the presence of flat pre-trends, as the coefficients are nearly aligned with the 0 line.

4.1 Mitigation vs Adaptation

Are inventors merely adapting to a changing environment (see, for instance, Miao and Popp 2014 and Moscona and Sastry 2023), or are they somehow internalizing the long-run costs of emissions? The patent data allows us to explore which type of green innovation inventors patent. To do so, we delve deeper into the subcategories of the Y02 classification.

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[12] class, "technologies for adaptation to climate change," and pool all the other Y02 subclasses.[13] The other subclasses are all related to mitigation. We find that the pattern for mitigation patents largely mirrors our main results, while the effect on adaptation technologies is comparatively muted. To the best of our knowledge, we are the first to document the effect natural disaster exposure has on mitigation technologies.

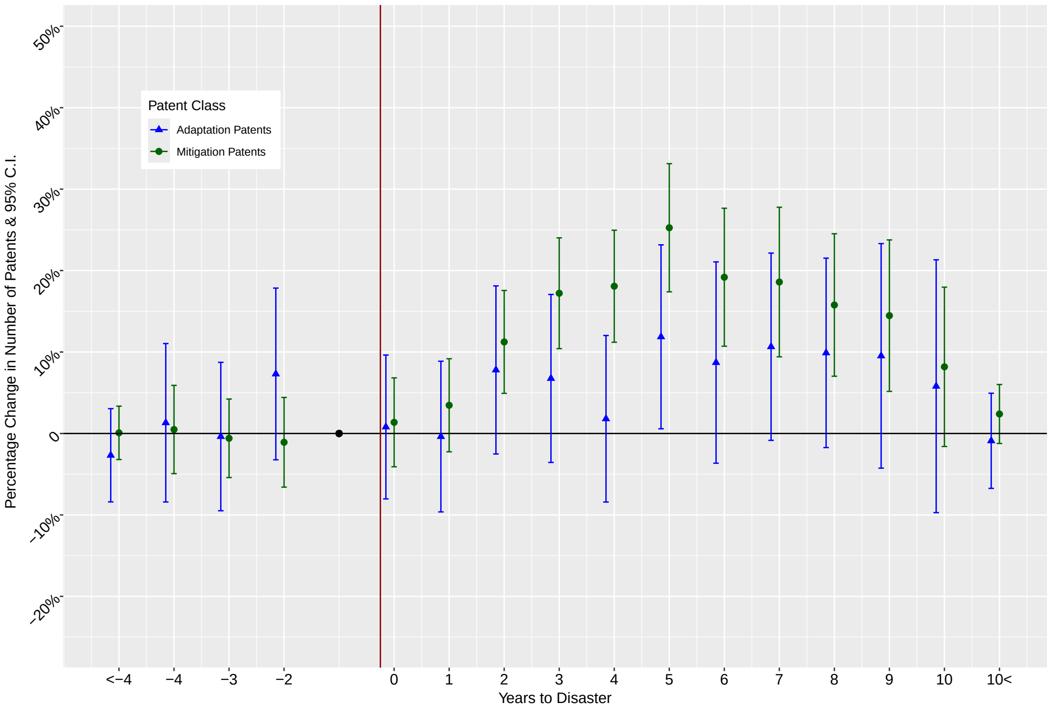

Figure 4: French and German Green Patenting Activity by Type

Note: 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. Standard errors are clustered on the region level and confidence intervals are drawn for the 95% interval.

In Appendix Section A.1, we additionally present results for all the subclasses in isolation. In our baseline difference-in-difference specification (6), the coefficient on the cumulative count of past disasters is always positive and significant for 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. We present our 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.

Table 1 presents the estimates for our difference-in-difference specification. In the long run, one additional natural disaster increases patenting in mitigation technologies

[12] We were recently made aware that the Y02A class might not be well labeled in PATSTAT, leading to many patents that should be in the CPC class not being labeled as such. However, it is unclear how better labeling would affect our results, as we are only comparing within the CPC class. Despite this, the comparison between the different classes remains of interest, as it highlights that innovation is not exclusively driven by technologies from class Y02A.

[13] See Appendix Section A.1 for an overview of all the Y02 classes used in this analysis.

by 8.6% compared to the sample average and patenting in adaptation technologies by 4.4%. We test whether these coefficients are statistically significantly different. We can reject the null-hypothesis of equality with a p-value of 0.0097.

Table 1

	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***	
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: Cumulative Count is the count of past natural disasters. Results are for our pooled country sample (France and Germany). We construct a Wald-test of the form $W = \frac{(\hat{\beta}_{\text{eq}1} - \hat{\beta}_{\text{eq}2})^2}{\text{Var}(\hat{\beta}_{\text{eq}1} - \hat{\beta}_{\text{eq}2})}$, where: $\text{Var}(\hat{\beta}_{\text{eq}1} - \hat{\beta}_{\text{eq}2}) = \text{Var}(\hat{\beta}_{\text{eq}1}) + \text{Var}(\hat{\beta}_{\text{eq}2}) - 2 \cdot \text{Cov}(\hat{\beta}_{\text{eq}1}, \hat{\beta}_{\text{eq}2})$. We can reject the Null hypothesis $H_0 : \beta_{\text{eq}1} = \beta_{\text{eq}2}$ against the alternative ($H_1 : \beta_{\text{eq}1} \neq \beta_{\text{eq}2}$) with the reported p value. 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

Inventors thus not only try to protect themselves against the adverse effects of climate change, but they patent ideas that help combat climate change in and of 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. We later show that these expectations about greater value stem from inventors' higher-order beliefs about consumer preferences and voting patterns.

4.2 Spillovers

Our main results provide preliminary evidence suggesting a lack of significant spillovers; if spillovers were present, the observed effects would likely be less pronounced. In this section, we further investigate if there are any significant spillovers between regions. To do so, we calculate the number of natural disasters in neighboring regions. Figure 5 depicts our different distance bands with which we consider a region to be a neighbor.

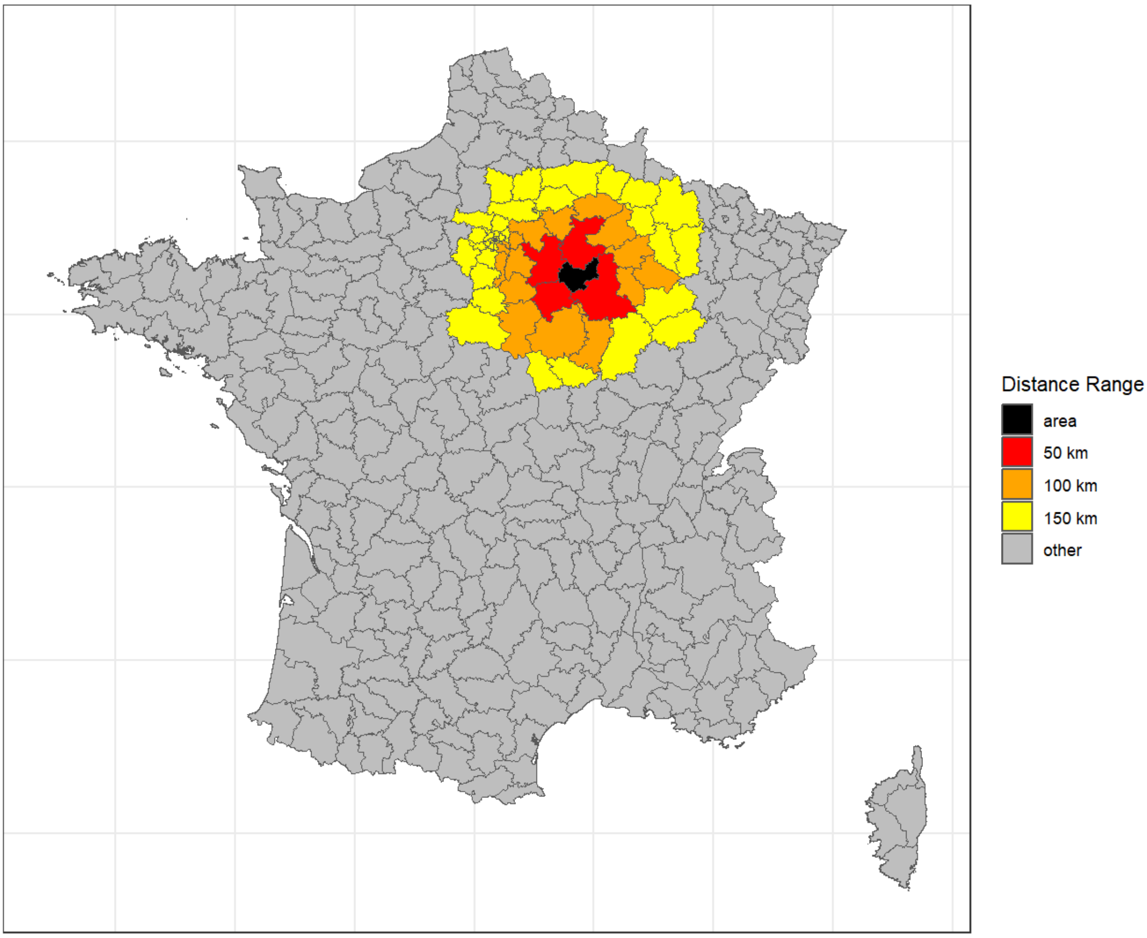

Figure 5: Illustration of Distances to Region

Note: Only showing France for simplicity.

Red-shaded areas are closer than 50km to the area of interest (black-shaded area), while orange-shaded areas are closer than 100km away. We run two separate types of regressions. First, we look at all regions that are less than 50, 100, and 150km away. When we consider regions that are, e.g., less than 150km away, we calculate the sum of all natural disasters in yellow-, orange-, and red-shaded regions. Additionally, we estimate a "donut" regression where, for 150km, we only look at regions that are less than 150km away but more than 100km away. We thus sum up only the natural disasters that occurred in yellow-shaded areas.

We then estimate our difference-in-difference specification (6) and depict the results in table 2. One additional disaster in a region closer than 50km away (thus in most cases directly adjacent) leads to a long-run increase in patenting of about 1.1%. Relative to the results presented in Table 1, the magnitude of the increase is approximately eight times smaller. When we move to natural disasters in regions that are 100km or 150km away, we find no sizeable effect. Similarly, when estimating our donut regression, we find no sizeable effect of natural disaster occurrence in regions that are more than 50km away.

Table 2: Spillovers of Neighboring Disasters

	Dependent variable:				
	$P(Y02_{lt})$				
	50km	100km	Donut 100km	150km	Donut 150km
	(1)	(2)	(3)	(4)	(5)
Cumulative Count Neighbor	0.011^{***}	-0.002^{***}		-0.001^{***}	
	(0.003)	(0.0003)		(0.0002)	
Cumulative Count Neighbor Donut			-0.003^{***}		-0.003^{***}
			(0.0003)		(0.0004)
Country-Year F.E.	Yes	Yes	Yes	Yes	Yes
Region F.E.	Yes	Yes	Yes	Yes	Yes
CPC Controls	Yes	Yes	Yes	Yes	Yes
Observations	15,813	15,813	15,813	15,813	15,813
R^2	0.738	0.737	0.738	0.738	0.738
Adjusted R^2	0.724	0.723	0.724	0.724	0.724

Note: "Cumulative Count Neighbor" 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 5. "Cumulative Count Neighbor Donut" is the disaster count only in the regions that are e.g. 100km away but not 50km away. This would correspond to only the orange regions in figure 5. Results are for our pooled country sample (France, Germany). 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

In columns (2) to (5), we find marginal negative effects, which are significant. A possible explanation is the way we estimate our difference-in-difference design. In our setting, we essentially regress patenting in the region of interest on the number of natural disasters in other regions. To some extent, we therefore invert our main specification of interest. The control group is now experiencing natural disasters, while the treated group is not. It is therefore natural to find somewhat negative effects. In typical singular treatment designs, it is straightforward to omit treated regions from the comparison group. As we have a panel of regions that are, for the most part, treated multiple times, this design is not straightforwardly applicable in our case.

The lack of spillovers is striking and gives credence to the direct personal experience of the inventor being the driving force behind our results.

In the following section, we show that the lack of spillovers also implies that observed innovation in response to natural disasters is inefficient. This is due to heterogeneity in expectations leading to heterogeneous innovation effort, with some inventors reacting strongly, while others do not react at all. Convexity in research costs then implies inefficient output compared to a situation where all inventors invest the same. The policy implication is that propagating local information can lead to welfare improvements. However, we do not take a stance on how feasible it is to spread information that is inherently tied to the personal experience of a natural disaster.

5 The Market for Green Goods

Our results in Figure 3 and Table 2 indicate two types of inefficiencies. First, natural disasters only have local effects rather than stimulating overall innovation activity. Put differently, the information does not propagate to unaffected regions and only impacts local inventors who have directly experienced the natural disaster. Second, while natural disasters are becoming increasingly frequent, our results show that innovation only accelerates when inventors are personally affected. Therefore, inventors do not fully internalize the long-run increase in climate change risk.

In the following, we discuss why inventors react to natural disaster exposure. Our theoretical framework highlights changes to affected inventors' expectations about market conditions and the profitability of green goods as the primary driver of the innovation response. In chapter 5.2, we confirm this using survey evidence from innovating firms in Germany. We show that, in the aftermath of natural disasters, firms update their expectations regarding future demand for green goods and anticipate more stringent environmental regulation.

We propose that exposure to natural disasters increases the local salience of environmental issues and climate change, which in turn shapes local inventors' expectations regarding environmental policy and the demand for green goods.

A growing body of research supports the idea that experiencing natural disasters positively influences beliefs in favor of environmental policies. For example, Djourelova et al. (2024) show that natural disaster exposure increases the prominence of environmental issues in news coverage. Similarly, Owen et al. (2012) find that the personal experience of natural disasters shape individuals' perceptions of climate change risks, leading to stronger support for environmental protection laws. In line with these findings, Osberghaus and Fugger (2022) demonstrate that residing in flood-prone areas—and experiencing the associated damages—positively affects beliefs about climate change. Moreover, Dechezleprêtre et al. (2022) highlight that environmental issues are especially salient in countries that are more vulnerable to and affected by climate change. Furthermore, natural disasters can lead to increased consumer demand for green products which then spurs innovation (Horbach 2008, Bossle et al. 2016). This increased salience matters for local inventors, who then observe not only heightened awareness but also increased support for environmental policies among their neighbors and friends.

The literature on personal experience and memory further shows that individuals often extrapolate from their own experiences to form expectations about aggregate outcomes. Perhaps most related to our work, Kuchler and Zafar (2019) illustrate that local experiences with house price changes affect expectations regarding national (U.S.) housing market trends. Similarly, Malmendier and Nagel (2011) reveal that individuals who have experienced low stock market returns are less inclined to take financial risks in the present. Finally, Gallagher (2014) document that the uptake of flood insurance increases significantly after an area is hit by a flood.

Additionally, belief updating among other stakeholders can stimulate green innovation. Stakeholders such as investors, or suppliers may develop a heightened preference for green innovation. For instance, a firm's shareholders may be affected by natural disasters and subsequently demand a strategy focusing more on climate change issues.

Clearly, inventors might also be influenced by intrinsic motivation or changes in public research funding. However, we show that, at least in France, there is no differential flow in government research funding following natural disasters. Furthermore, German innovating firms do not report increases in government funding as a reason for heightened green innovation. German firms are significantly more likely to join a voluntary "green" standard after experiencing a natural disaster. This could be driven either by intrinsic motivation or by efforts to attract customers, for instance, through eco-friendly labeling.

In line with our model, market conditions for green products matter greatly. We find that almost all of the increase in green innovation is driven by patents from years where industries were most competitive. Additionally, we find that there is a larger response in sectors where these goods are already valued.

To better shed light on the mechanism, we construct a theoretical framework that adapts and extends the model proposed in Aghion et al. (2023). The essence of their model is that consumers' environmental preferences lead to higher demand for green goods, which spurs innovation efforts. This effect also interacts with competition, as firms facing intense competition with their current product lines gain greater benefits from "escaping" market competition by introducing greener and thus distinct products. We additionally allow for uncertainty over future demand. Additionally, we incorporate regional variation in inventor expectations, which are influenced by natural disaster exposure.

5.1 Model

In our model, there are two ways in which natural disasters can affect inventors' expectations about the profitability of a green innovation. First, consumers are environmentally conscious. They care not only about the consumption value of a good but also about their own carbon footprint when consuming that good. These preferences can, for instance, arise from social image concerns, a general sense of responsibility toward the environment, etc. This is modeled as consumers having quality-adjusted taste-for-variety preferences. In our setting, the quality of a good is simply the inverse of emissions, $q_j = 1/x_j$, where x_j represents the emissions produced when generating one unit of good j. Individual utility is then given by

$$U = \int_0^1 \ln \bar{y}_j \, dj, \tag{7}$$

with

$$\bar{y}_j = \int_{f \in \mathcal{F}_j} y_{j,f} \left(q_{j,f}\right)^{\delta_j} \, df, \tag{8}$$

where $\bar{y}_j$ is the quality-adjusted consumption of good j, which can be purchased from various firms $f \in \mathcal{F}_j$. Put simply, individuals care about both the consumption value of a good and the emissions associated with it.

Second, the value of a green product positively depends on the stringency of environmental regulation, as stricter policies increase the costs of the "non-green" alternative. In our model, δ_j thus represents the overall profitability in terms of demand and emissions savings that an innovator can expect for a good of quality $q_{j,f}$. The term δ_j thus captures how individuals value their own private consumption as well as how they express their political preferences regarding environmental policy. As previously mentioned, exposure to natural disasters shifts local preferences for environmental policy upward. δ_j is potentially heterogeneous across goods. For instance, consumers might care differently about their carbon footprint when purchasing meat and its vegetarian alternatives than when buying toothpaste. This variation can be due to differences in awareness or labeling (Agatz et al. 2021, Duckworth et al. 2022). Additionally, climate policy is often sectorial to protect national interests or to appease a certain group of voters.

Varieties j are imperfect substitutes, while within a variety, all demand will go to the firm with the highest quality-to-price ratio, q^{δ}/p. Logarithmic preferences imply that expenditure is uniform across all varieties. We assume that consumer demand is non-local. Thus, once a product is patented it can/will be marketed globally. Although this is a strong assumption, we demonstrate that our results remain valid when focusing exclusively on globally marketed patents (see Section 6.1 for results on triadic patents, which are filed globally). The Paris Convention for the Protection of Industrial Property (1883) adopted near universally, stipulates that an inventor who patents a product in one country can apply for protection in other contracting states within 12 months, with those applications receiving the same priority as the original filing. This allows for easier international market entry without the risk of losing rights to others. Even if an inventor does not choose to patent their invention in some countries, the same invention can not be patented there by others and is instead regarded as public information accessible to all.

Environmental profitability δ_j evolves over time, and there exists local uncertainty regarding the extent of future profitability. The global level of δ could, for instance, depend on the degree of global exposure to climate change. Firms and inventors are local and form Bayesian expectations about environmental profitability according to a prior ρ (common across all locations) and local l events D_l:

$$E_l[\delta_j] = \alpha\rho + (1-\alpha)\phi D_l, \tag{9}$$

where ϕ denotes the size of the information shock. Both the inventors' expectations and consumers' environmental preferences can thus fall whenever they are unaffected (for consumers in the aggregate) by natural disasters. We can then formulate the following empirically testable hypothesis:

Hypothesis 1: Inventor expectations about consumer demand, and the stringency of environmental regulation increase following natural disaster exposure.

To do welfare analysis, we solve a welfare maximization problem with respect to the optimal innovation rate from a social planner perspective. The social planner observes all local natural disasters and then forms aggregate beliefs according to:

$$\hat{E}[\delta_j] = \alpha\rho + (1-\alpha)\int_l \phi D_l f(l)dl = \alpha\delta_j + (1-\alpha)\phi\overline{D_l} = \int_l E_l[\delta_j]f(l)dl = \overline{E_l[\delta_j]} \quad (10)$$

where $f(l)$ is the probability density function across regions l. In the following, we denote $\hat{E}$ as the social planner expectation.

There can thus be some inventors in regions exposed to natural disasters who have expectations above the social planner's ($E_l[\delta_j] > \hat{E}[\delta_j]$), or inventors in regions without natural disaster exposure where $E_l[\delta_j] < \hat{E}[\delta_j]$. However, on average, the social planner simply aggregates local expectations.

The only input is labor, supplied infinitely elastically at wages normalized to 1. Thus, firms only face labor costs c when producing one unit of output. The production process emits $1/q$ emissions.

The quality of a 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 the cumulative number of previous innovations made in that good. In essence, γ denotes by how much a good of variety j improves when green innovation is successful. Sectors consist of a duopoly and a competitive fringe that disciplines market participants. The competitive fringe produces goods γ times more polluting than the duopolists and is therefore one innovation period behind. As in Aghion et al. (2023), every period, only one of the competitors has the opportunity to invest in research. For any level of research effort $z_j \leq 1$, investing $\kappa z_j^2/2$ units of labor yields, with probability z_j, a green innovation.[14] This innovation improves the quality of good y in the following period by γ. With probability $1 - z_j$ research efforts fail and yield no progress.

Whenever an inventor successfully innovates, they receive a patent for that improved good. The successful inventor then has a quality advantage over the follower, enabling her to engage in limit pricing where setting the price to $p_M = \gamma^{\delta}c$ captures all demand. This essentially makes successful innovators the monopolist in the following period.

[14] We deem convex innovation costs a reasonable assumption, as reducing the environmental impact of goods becomes increasingly more costly. For example, making planes fly with less fuel is easier than making a plane that does not consume any fuel or emit CO_2.

Patents, in turn, expire after one period, thus resetting the market to a situation where there is no quality difference between competitors' goods. As the content of patents is common knowledge, innovators can invest in research starting at the "cutting edge" today, even if they are not the current monopolist.

At the time of investing in research, local inventors expect to have output and profits when being successful in their research:

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

where $E_l[\delta_j]$ is the local expectation of the environmental profitability (see equation (9)). Thus, if inventors expect higher consumer demand and stronger preferences for environmental policy, their price and profit expectations increase.

Accordingly, the social planner has expectations:

$$\hat{E}[y_{Mj}] = \frac{1}{E[p_{Mj}]} = \frac{1}{\gamma^{\overline{E[\delta_j]}}c}, \quad \hat{E}[\pi_{Mj}] = 1 - \frac{1}{\gamma^{\overline{E[\delta_j]}}}. \tag{12}$$

where $\gamma^{\overline{E[\delta_j]}}$ is the expectation of how much the market and thus the average consumer values a quality improvement of γ in good market j.

In a good market where no innovation occurs, the duopolists engage in price competition. If they collude perfectly, they can charge the monopoly price and split the profits among themselves. They cannot charge more than the monopoly price, since they are disciplined by the competitive fringe, which would enter the market whenever the mark-up is larger than a one-period innovation gap. If, on the other hand, the duopolists engage in "full" competition, they bid down the price to the production cost. Following Aghion et al. (2005), we model competition as the degree to which the two duopolists can collude. Duopoly profits then depend on the level of competition Δ_j in market j:

$$E_l\left[\pi_{Dj}(\Delta_j)\right] = (1-\Delta_j)E_l\left[\pi_{Mj}\right] \tag{13}$$

with $\Delta_j \in [1/2, 1]$ lying on the set between the full-competition and collusion case. For $\Delta_j = 1$ we are in the setting of Bertrand competition, whereas in the case of $\Delta_j = 1/2$ we have full collusion.

The locally expected duopoly price in is then:

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

and the expected output is:

$$E_l[y(\Delta_j)] = \frac{1}{E_l[p_j](\Delta_j)} = \frac{1}{c}\left[1-2(1-\Delta_j)\left(1-\gamma^{-E_l[\delta_j]}\right)\right] \in \left[E_l[y_{Mj}], \frac{1}{c}\right] \tag{15}$$

and equivalently for the social planner:

$$\hat{E}[p_j(\Delta_j)] = \frac{c}{1-2(1-\Delta_j)\hat{E}[\pi_{Mj}]}, \hat{E}[y(\Delta_j)] = \frac{1}{\hat{E}[p_j](\Delta_j)} \tag{16}$$

A local firm in sector j with an R&D opportunity maximizes

$$\max_{z_{lj}\in[0,1]} \left\{ z_{lj}E_l\left[\pi_{Mj}\right] + (1-z_{lj})E_l\left[\pi_{Dj}(\Delta_j)\right] - \kappa z_{lj}^2/2 \right\} \tag{17}$$

where success yields monopoly profits, and failure to innovate 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 thus acts as a wedge between the profits of an innovative firm, and the profits firms can reap in the status quo. The first-order condition of a local firm with respect to the research rate is:

$$z_{lj} = \min\left\{ \frac{E_l\left[\pi_{Mj}\right] - E_l\left[\pi_{Dj}(\Delta_j)\right]}{\kappa}, 1 \right\}. \tag{18}$$

From (18) with (11) and (13), we get:

$$z_{lj}(\Delta_j, E_l(\delta_j)) = \frac{\Delta_j E_l\left[\pi_{Mj}\right]}{\kappa} = \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right). \tag{19}$$

The locally chosen innovation rate thus depends positively on the degree of competition Δ_j and local inventors' expectations about the profitability of green innovation $E_l[\delta_j]$. A brief example: when in expectation, consumers attach no value to a good $\tilde{j}$ being green, and there is no policy valuing the greenness of that good, inventors expect $E_l[\delta_{\tilde{j}}] = 0$. The optimal research rate in good market $\tilde{j}$ is then $z_{l\tilde{j}}(\Delta_j, E_l(\delta_{\tilde{j}})) = 0$.

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

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

Let

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

denote the research rate that would be achieved if all local inventors had the same (average across regions l) expectation on future environmental profitability. We can then compare $\overline{z}(\Delta_j)$ with the aggregate private research rate $\underline{z_t}(\Delta_j)$.

Proposition 1: As long as at least one region is affected differently than the rest we get that the research rate achieved under average expectations is larger than the research rate achieved when expectations are heterogenous across regions.[15]

$$\overline{z}(\Delta_j, \overline{E_l(\delta_j)}) = \int_j \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{\overline{E_l(\delta_j)}}}\right) f(j)dj >$$
$$\underline{z}(\Delta_j, E_l(\delta_j)) = \int_j \int_l z_{jl}(\Delta_j, E_l[\delta_j]) f(l) dl f(j) dj = \int_j \int_l \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) f(l) dl f(j) dj \tag{20}$$

Proof of Proposition 1: Since $\gamma > 1$ and $\forall E[\delta_j] > 0$, we have that $\left(1 - \frac{1}{\gamma^{E[\delta_j]}}\right)$ is strictly concave in $E[\delta_j]$. By a straightforward application of Jensen's inequality, we have that $\forall j$:

$$\frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{\overline{E_l(\delta_j)}}}\right) > \int_l \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right) f(l)dl \tag{21}$$

This highlights the inefficiency due to the local character of belief updating. Having average beliefs across inventors, thus spreading information beyond affected regions, would either yield higher research output for the same cost, or lower costs for the same research output. Intuitively, this is due to convex costs of research effort.

Mirroring Proposition 1 of Aghion et al. (2023), we find that $\frac{\partial \overline{z}}{\partial \Delta_j} > 0$, $\frac{\partial \underline{z}}{\partial \Delta_j} > 0$, and $\frac{\partial \overline{z}}{\partial E[\delta_j]} > 0$, $\frac{\partial \underline{z}}{\partial E[\delta_j]} > 0$. Moreover, due to the positive cross-derivatives, these forces are complements: $\frac{\partial^2 \overline{z}}{\partial \Delta_j \partial E[\delta_j]} > 0$, $\frac{\partial^2 \underline{z}}{\partial \Delta_j \partial E[\delta_j]} > 0$.

Hypothesis 2: Inventors facing fiercer competition adjust their research output more whenever their profitability expectations change due to exposure to a natural disaster.

This result allows us to empirically test our model by comparing the evolution in treated regions between high-competition and low-competition patents (see table 4 for our empirical results on this hypothesis).

5.1.1 Building on the Shoulders of Giants & Market Size

In this section, we incorporate insights from the literature on directed technical change, whereby the profitability of innovation increases in the size of the market for that type of technology. This is often termed as the "building on the shoulders of giants" feature of innovation (see Acemoglu 2002; Acemoglu 2007, and for an application to green technology Acemoglu et al. 2012). To do so we explicitly model the cost of research 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.2 in the 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.

From equation (19) we have that the optimal private research rate is chosen ac-

[15] One region being affected differently simply means that $\exists l$ s.t. $E_l(\delta_j) \neq \overline{E_l(\delta_j)}$.

cording to:

$$z_{lj}(\Delta_j, E_l(\delta_j), \eta_j) = \frac{\Delta_j E_l\left[\pi_{Mj}\right]}{K(\eta_j)} = \frac{\Delta_j}{K(\eta_j)}\left(1 - \frac{1}{\gamma^{E_l[\delta_j]}}\right). \tag{22}$$

Trivially, 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: $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial E_l(\delta_j)} > 0$. This allows us to formulate an additional hypothesis, analogous to the case of competition:

Hypothesis 3: Innovation responses are stronger in markets where green goods have already proliferated.

5.1.2 Welfare

We now turn our eye to societal welfare. Societal welfare depends on quality-adjusted consumption (7) 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:

$$X = \int_j (1 - z_j) y(\Delta_j) + z_{lj} y_{M_j}/\gamma dj \tag{23}$$

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 $\psi > 0$. 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:

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

The condition

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

stipulates that research costs do not exceed firm profits and acts as a sort of resource constraint. λ then gives the degree to which firm profits can be traded off against research costs. Put differently, λ denotes the value the social planner attaches to innovators' profits. When $\lambda \to \infty$, the social planner simply maximizes firm profits.

Proposition 2: 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.

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

Broken down by its components, the socially optimal research rate $z_j^*(\Delta_j, \eta_j)$ 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.

Proof of proposition 2: While proposition 1 (equation 20) does not have heterogeneous market size, it is trivial to extend to this case, resulting in the following condition:

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

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

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

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 (12) to $\hat{E}[y_{M_j}]\gamma^{\overline{E[\delta_j]}} = \frac{1}{c}$, which, together with (15), 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 trivially since from (15) we get that $y_j(\Delta_j) \geq y_{M_j}$ $\forall \Delta_j \in [1/2, 1]$ and we additionally have that $\gamma > 1, \psi > 0$.

This emphasizes the inefficiency of only updating according to local information. Additionally, this inefficiency is scaled by market size. When the market for green goods grows and incentive to do research increase, local updating becomes more and more inefficient. We believe that a real policymaker can likely observe more, if not all, natural disasters and thus form better expectations than local inventors can. Therefore, there is clearly scope for policy to act by either propagating the information of natural disasters beyond the affected inventors or, alternatively, incentivizing research in unaffected regions. Based on the optimal research rate of the social planner, additional information would 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 $\hat{E}[\delta] > \overline{E_l[\delta]}$, then there is further scope for policy by correcting these inefficiently 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.

5.2 Expectations

According to our model, the primary channel through which natural disasters affect inventors is by shaping their expectations about the profitability of environmental goods. In the following, we explicitly test hypothesis 1 of our model. Using firm-level survey data from the Community Innovation Survey (CIS), we test this empirically. To capture the role of expectations, we create two distinct variables: one for expected environmental regulation and another for current and expected demand for green goods. These variables are based on the survey question: "During [the past two years], how important were the following factors in driving your enterprise's decision to introduce innovations with environmental benefits?" Firms could indicate one of four levels of importance: high, medium, low, or not relevant. For our analysis, we construct a dummy variable for each factor, assigning a value of one if a factor was rated as low, medium, or high in importance and zero if it was deemed irrelevant to the introduction of green innovation. Section A.7.2 provides detailed information on the variable construction.

We are interested in the effect of natural disasters on firms' expectations. To estimate this effect, we use the following equation:

$$Y_{ilt} = \beta \left(\sum_{s=0}^{X} T_{l,t-s} \right) + \gamma_1 \mathbf{S}_{it} + \gamma_2 R_{it} + \gamma_3 \lambda_t + \gamma_4 \lambda_k + +\epsilon_{it} \tag{28}$$

Here, Y_{ilt} represents a dummy variable indicating whether the respective factor for green innovation was considered important by firm i in year t exposed to natural disasters in region l. Our primary explanatory variable, $\left(\sum_{s=0}^{X} T_{l,t-s}\right)$, is the count of recent natural disasters occurring over the past $X \in 3, 10, \infty$ years. For robustness sake, we run three separate regression for each of those time frames. When $X = \infty$ our primary explanatory variable is similar to our baseline cumulate disaster specification in equation (6). Treatment is then the cumulative count of past natural disasters. However, the CIS does not represent a panel dataset of firms; instead, it comprises a repeated cross-section of firms. We therefore prefer estimating the same equation with a time span of 3 and 10 years respectively. We account for firm's revenue, denoted as R_{it}, in a specified year and include firm-size dummies $\mathbf{S}_{it}$ 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. Additionally, we include year and industry fixed effects based on the NACE Rev2 two-digit industry codes. Standard errors are clustered by NUTS regions (level 3), corresponding to the German "Kreise."

The questions in the CIS generally pertain to the preceding two years; for example, in the survey conducted in 2009, the questions relate to innovations occurring between 2006 and 2008. Consequently, we calculate the count of past disasters starting from 2006 and include disasters from 2004-2006 for our treatment variable (with $X = 3$). The results remain robust if we adjust the reference year to 2007 and incorporate all disasters from 2005-2007.

Table 3: Effect of Natural Disasters on Firm's Expectations

	Dependent variable:					
	Expected Regulation ↑	Expected Demand ↑	Expected Regulation ↑	Expected Demand ↑	Expected Regulation ↑	Expected Demand ↑
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Count	0.00592***	0.00439**				
	(0.00205)	(0.00184)				
Disaster Count Last 3 years			0.0250***	0.00919**		
			(0.00459)	(0.00441)		
Disaster Count Last 10 years					0.00760***	0.00394*
					(0.00215)	(0.00206)
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
Observations	14067	14033	14,067	14,033	14,067	14,033
R^2	0.444	0.387	0.445	0.387	0.444	0.387
Adj. R^2	0.441	0.384	0.442	0.384	0.441	0.383

Note: Cumulative Count is the cumulative count of past natural disasters. "Disaster Count Last 3 Years" is the count of natural disasters in the past 3 years. "Disaster Count Last 10 Years" is the count of natural disasters in the past 10 years. Firm Size is a vector of dummies for a firm being small, medium or large dependent on the number of employees. Standard errors are clustered on the region (Kreis) level and are reported in parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

The findings presented in Table 3 corroborate our theoretical model, demonstrating that firms update their expectation about upcoming regulations and future green good demand in response to natural disaster exposure. The results of our preferred specification in column (3) imply that one additional natural disaster in the past 3 years increases the likelihood that a firm will cite more stringent expected regulation as a primary reason for their green innovation efforts by 2.5 percentage points. Similarly, column (4) indicates that exposed firms are 0.9 percentage points more likely to cite higher expected demand as a primary reason for innovation. Across columns, the point estimates change. This is due to the number of natural disasters in our treatment variable changing when we move from e.g. the last 3 to the last 10 years.

5.3 Market Conditions

In addition to inventors' expectations, we further investigate how market conditions shape inventors' responses to natural disaster exposure. Our findings reveal that a well-functioning market is essential to ensure that inventors respond to new information about climate change.

5.3.1 Competition

First, we turn our attention to hypothesis 2 of our model, namely, that inventors in competitive industries should respond more strongly 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.

To test our hypothesis empirically, we use data from CompNet (2022) on industry-level competition for Germany and France. Following Aghion et al. (2023), we use (inverse) profit margins as an indicator of competitiveness. This modeling choice follows closely how competition is modeled in our model framework. We have data at the 2-digit NACE level, which allows us to link yearly industry-level profit margins to the patent data. For each patent, we calculate the associated profit margin $M(i)$ of patent i as:

$$M_{it} = \sum_c \omega_{ic} \sum_k w_{ik} \times \frac{(margin_{kc,t} + margin_{kc,t-1})}{2} \tag{29}$$

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 Appendix Section A.4, we show our results for the 1-year and 3-year windows of the profit margin.

One important distinction from earlier sample splits is that, instead of splitting the sample simply by its mean, we split the sample within each industry. Specifically, rather than comparing patents from, for example, the very competitive LED industry with those from the less competitive airline industry, we compare patents from the LED industry during its most competitive periods against its less competitive years. We therefore split the sample into above- and below-median competition levels within each industry. To achieve this, we calculate the median level of competition for each 2-digit NACE industry and assign each patent an individual benchmark based on the industries to which it belongs. The benchmark competition (BMC) is computed as follows:

$$BMC_i = \sum_c \omega_{ic} \sum_k w_{ik} \times \text{median}(margin_{kc,t \in T}) \tag{30}$$

If patent i's margin M_{it} is larger than the benchmark BMC_i, we assign it to the high-competition sample; otherwise, it is assigned to the low-competition sample. As a result of this procedure, our samples have different sample averages. Since we divide our outcome variable by the sample average, the results are still comparable.[16] Table 4 depicts our results.

Table 4: Competition Split

	Dependent variable:	
	$P(Y02_{lt})$	
Competition Cutoff:	High-Competition	Low-Competition
	(1)	(2)
Cumulative Count	0.104***	0.007
	(0.022)	(0.033)
Country-Year F.E.	Yes	Yes
Region F.E.	Yes	Yes
CPC Controls	Yes	Yes
Wald-test p-value:	0.0365**	
Sample Mean	1.9854	1.284
Observations	8,283	8,283
R^2	0.653	0.535
Adj. R^2	0.617	0.486

Note: Cumulative count is the count of past natural disasters. We test the null hypothesis that the Disaster Count coefficient is larger for our sample of above-median competition patents than 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 values. In Germany and France, the average number of patents per region with above/below median level of competition in it's associated industry is 1.9854 and 1.284 respectively. Competition is measured as the average across the filing year and the year before filing. 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

[16] Since the results are such that there seems to be no effect on patents from low-competition years, we are confident that our procedure should not interfere either way.

Inventors react significantly more to natural disaster exposure in high-competition environments than they do in low-competition environments. We interpret our results as strong evidence supporting our hypothesis and corroborating our theoretical model. The difference between inventors' responses to natural disaster exposure in high- and low-competition environments is both large and significant. We can reject the null hypothesis of coefficient equality with a p-value of 0.0365** (see the note in Table 4 for our Wald-test).

In particular, the absence of effects in low-competition environments speaks to pecuniary incentives mattering most for our observed innovation response. The competitive environment should not matter for mostly intrinsically motivated inventors. Our results indicate that functioning competitive markets are essential to ensuring that innovation responds to climate change.

5.3.2 Green Good Demand

Next, we examine the size of the green goods market across different industries. Specifically, we test Hypothesis 3 of our model, which posits that a larger market size strengthens incentives to innovate following exposure to a natural disaster. The intuition behind this hypothesis aligns with the literature on endogenous technical change, particularly the concept of "building on the shoulders of giants." In his seminal papers on the topic (Acemoglu 2002; Acemoglu 2007), Acemoglu argues that as market size expands, innovation within that market becomes increasingly profitable. We proxy market size by measuring the share of green goods within a given market. This modeling approach is most closely related to Acemoglu et al. (2012) and Acemoglu et al. (2016), where the size of the green market is shown to have a strong positive impact on incentives to innovate in that specific market. While our proxy is undoubtedly imperfect, it helps identify the types of markets where inventors are more likely to pursue green innovation following exposure to a natural disaster.

Following Bontadini and Vona (2023) and using PRODCOM data, we compute an industry's green product share as:

$$\text{Green Share}_{jt} = \frac{\sum_g y_{jt,g}}{\sum_g y_{jt,g} + \sum_{ng} y_{jt,ng}} \tag{31}$$

We then assign each patent i a green share value depending on the industries to which patent i is assigned. Patents can be assigned to multiple industries and have different weights for each industry. We calculate a patent's green share as:

$$\text{Green Share Patent}_i = \sum_j \text{Green Share}_{jt}\omega_{ij} \tag{32}$$

where t is the year of the patent filing and ω_{ij} is the weight with which patent i belongs to industry j. In essence, we split the sample of green patents by how green their corresponding industries are at the time of patent filing. Based on this sample split we regress two separate regression, the results of which are depicted in table 5.

Table 12 in the appendix depicts our results when the green product share is based only on the year of filing, and when it is calculated on a 3 year window. Results are qualitatively the same.

Table 5: Green Product Analysis - Above/Below Median

	Dependent variable:	
	$P(Y02_{lt})$	
Greenness Cutoff:	Above Median	Below Median
	(1)	(2)
Cumulative Count	0.088***	0.063***
	(0.011)	(0.009)
Country-Year F.E.	Yes	Yes
Region F.E.	Yes	Yes
CPC Controls	Yes	Yes
Wald-test p-value:	0.0307**	
Sample Mean	1.335	1.3248
Observations	14,307	14,307
R^2	0.625	0.788
Adj. R^2	0.603	0.776

Note: Cumulative Count is the count of past natural disasters. For each industry, we calculate the average green product share over the last 2 years. Results are for our pooled country sample (France and Germany) for the years 1996–2014. We only have PRODCOM data starting in 1995, so a 2-year window allows us to estimate starting in 1996. 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 $W = \frac{(\hat{\beta}_{eq1} - \hat{\beta}_{eq2})^2}{\mathrm{Var}(\hat{\beta}_{eq1} - \hat{\beta}_{eq2})}$, where: $\mathrm{Var}(\hat{\beta}_{eq1} - \hat{\beta}_{eq2}) = \mathrm{Var}(\hat{\beta}_{eq1}) + \mathrm{Var}(\hat{\beta}_{eq2}) - 2 \cdot \mathrm{Cov}(\hat{\beta}_{eq1}, \hat{\beta}_{eq2})$. 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. The average number of patents per region with above/below median level of green products in it's associated industry is 1.335 and 1.3248 respectively. 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

We find that market size matters. Inventors in industries where green goods have already proliferated respond more strongly to natural disasters than those in industries where such goods are less prominent. Our findings align with what the directed technical change literature puts forward. Mainly, market size determines incentives to innovate. As market size and inventor expectations are compliments, effects are markedly stronger in larger green good markets.

5.3.3 Regulation

We also examine the importance of existing environmental regulations, such as taxes, charges, and fees, in the context of the introduction of green innovations subsequent to natural disasters. To investigate this relationship, we follow the estimation strategy outlined in section 5.2. In the CIS survey, firms are asked about the importance of these existing regulations for the introduction of green innovation. We utilize this information to create an outcome variable that indicates whether existing regulations were a significant factor in the introduction of green innovations. Our results, presented in table 6, clearly demonstrate that existing environmental taxes, fees, and charges play an important role in facilitating green innovations after natural disasters.

Table 6: Effect of Natural Disasters on Firm's Awareness of Environmental Regulation

	Dependent variable:	
Awareness of:	Existing Regulation	
	(1)	(2)
Disaster Count Last 3 Years	0.0175*** (0.00474)	
Disaster Count Last 10 Years		0.00466** (0.00213)
Year F.E.	Yes	Yes
Firm Size F.E. (employment)	Yes	Yes
Revenue	Yes	Yes
Industry F.E. (2-digit NACE)	Yes	Yes
Observations	14,151	14,151
R^2	0.468	0.468
Adj. R^2	0.465	0.465

Note: "Disaster Count Last 3 Years" is the count of natural disasters in the past 3 years. "Disaster Count Last 10 Years" is the count of natural disasters in the past 10 years. Firm Size is a vector of dummies for a firm being small, medium or large dependent on the number of employees. Standard errors are clustered on the region (Kreis) level and are reported in parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

Overall, our findings suggest that natural disasters not only shape expectations but also heighten awareness of existing environmental regulations. This is likely driven by the increased salience of climate change and related policies. As a result, experiencing a natural disaster prompts firms to mitigate the costs of environmental regulations by developing new green innovations.

5.4 Alternative Explanations

5.4.1 Research Funding

Public subsidies play a crucial role in driving firms' engagement in green innovation (Bossle et al. 2016; Horbach 2008). In the aftermath of a natural disaster, policymakers may introduce new research subsidies to stimulate the development of environmentally friendly technologies.

Newly implemented subsidies or regional standards may directly encourage green innovation. Additionally, demand for existing funding sources may increase following a natural disaster, as firms seek additional support for adaptation and mitigation efforts.

To address the concern that public research funding might drive our findings, we analyze two datasets. First, we estimate the effect of natural disaster exposure on the demand for public research funding using survey data from the CIS.

As outlined earlier, we focus on firms' responses regarding the key factors influencing their participation in green innovation. We apply the estimation strategy detailed in Section 5.2. The results in columns (1) and (2) in table 7 imply that following natural disaster exposure that firms are not significantly more likely to state that public and subsidies played a role for their innovation effort. This holds for both natural disaster exposure in the past three or ten years.

Table 7: Other Potential Mechanisms - Survey Data

	Dependent variable:					
	Public Funding		Voluntary Standard		Reputation	
	(1)	(2)	(3)	(4)	(5)	(6)
Disaster Count Last 3 Years	0.00559 (0.00366)		0.0127*** (0.00429)		-0.000463 (0.00778)	
Disaster Count Last 10 Years		0.00126 (0.00173)		0.00528*** (0.00196)		0.00140 (0.00323)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm Size F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Revenue	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,052	14,052	14,058	14,058	8,409	8,409
R^2	0.335	0.334	0.427	0.427	0.530	0.530
Adj. R^2	0.331	0.331	0.423	0.423	0.526	0.526

Note: "Disaster Count Last 3 Years" and "Disaster Count Last 10 Years" refer to the number of natural disasters occurring in the respective periods. Firm Size F.E. is a vector of dummies for firm size (based on employment). Industry fixed effects are on the 2-digit NACE level. Standard errors are clustered on the region (Kreis) level and are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01.

Second, we match administrative data on French research funding to regions affected by natural disasters using data from scanR. ScanR is an online platform[17] curated by the Ministry of Higher Education and Research[18], providing a detailed overview of French research funding.

For our analysis, we construct two measures of research funding. First, we count the number of distinct research funding streams allocated to each region annually. Second, we calculate the total funding budget (in euros) flowing into a given region. Crucially, these measures capture research funding specifically, excluding financial aid intended for infrastructure rebuilding or disaster recovery. To examine the impact of natural disasters on research funding, we estimate a Difference-in-Differences regression. We use either (i) the cumulative number of past natural disasters—our preferred measure—or

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

[18]In French: Ministère de l'Enseignement supérieur et de la Recherche

(ii) the total number of disasters occurring within the last three years.

Table 8: French Research Funding

	Dependent variable:			
	Count	Budget	Count	Budget
	(1)	(2)	(3)	(4)
Cumulative Count	0.254	−1,224,154		
	(0.385)	(1,248,441)		
Disaster Count Last 3 Years			−0.365	−165,051
			(0.325)	(1,227,972)
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: 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. The results are 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

Table 8 reports our results. There is no significant effect on funding counts or on the funding budget a region receives after being exposed to a natural disaster. We take our results as indicative of the fact that green research is not driven by increased government spending on research efforts in the affected region. However, this does not necessarily imply the absence of increased government subsidies after natural disasters. It only implies that government research funding is not selectively channeled into the affected region.

5.4.2 Intrinsic Motivation

Intrinsic motivation refers to the idea that there is no reward for an activity other than the activity itself. Firms might engage in green innovation based on ethical values or sustainability goals, independent of external rewards or pressure. Natural disasters can also impact a firm's values and goals, thereby increasing green innovation activities. We use two different measures to assess firms' intrinsic motivation: the importance of reputational concerns and voluntary standards, based on data from the German part of the Community Innovation Survey (see Appendix A.7.2 for variable descriptions). Firms might be intrinsically motivated to have a positive impact on their environment and therefore engage in green innovation. However, firms might also want to improve their reputation and brand value by signaling these values to consumers. Our data does not allow us to distinguish between these two motives. We proxy intrinsic motivation by assessing the importance of voluntary industry standards for green innovation activities, as firms may be committed to sustainability beyond regulatory requirements. We follow the estimation strategy outlined in section 5.2. Table 7 shows that inventors exposed to natural disasters are more likely to join a voluntary industry standard. However, natural disaster exposure does not affect inventors' reputational concerns.

6 Heterogeneity & Robustness

6.1 Patent Value

To further corroborate our results, we begin by examining the value of patents created in the aftermath of natural disasters. When firms have established R&D facilities, acquiring a patent becomes relatively straightforward. Thus, the question arises: are firms merely capitalizing on the green trend following natural disasters, perhaps patenting some innovations that were already in the pipeline but hold less significance for technological progress, development, or innovative contributions? Similarly, individuals may patent spur-of-the-moment ideas that only have local value.

To show that we capture meaningful innovation, we turn to assess traditional indicators of patent value. One common measure is to use the number of citations a patent receives after publication as a proxy for its value. Patent citations refer to related technologies that are incorporated or referenced within a patent. Trajtenberg (1990) demonstrate in their seminal paper focusing on a particular innovation (computed tomography scanner) that patent citations are informative of the social value of innovations. Hall et al. (2005) illustrate that patent citations can predict the market value of a patent. Moreover, Harhoff et al. (1999) show that patent citations are correlated with the price at which patent holders are willing to sell the patent rights. Recent research also confirms that patent citations serve as a reliable predictor of patent quality (Jaffe and Rassenfosse 2017).

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 $\tilde{G}_{jt}$. We then say a patent i

belonging to CPC classes j and k received above the median number of citations if

$$\text{Citations}_{it} > \frac{\tilde{G}_{jt} + \tilde{G}_{kt}}{2}. \tag{33}$$

Figure 6 plots our baseline event study for both samples.

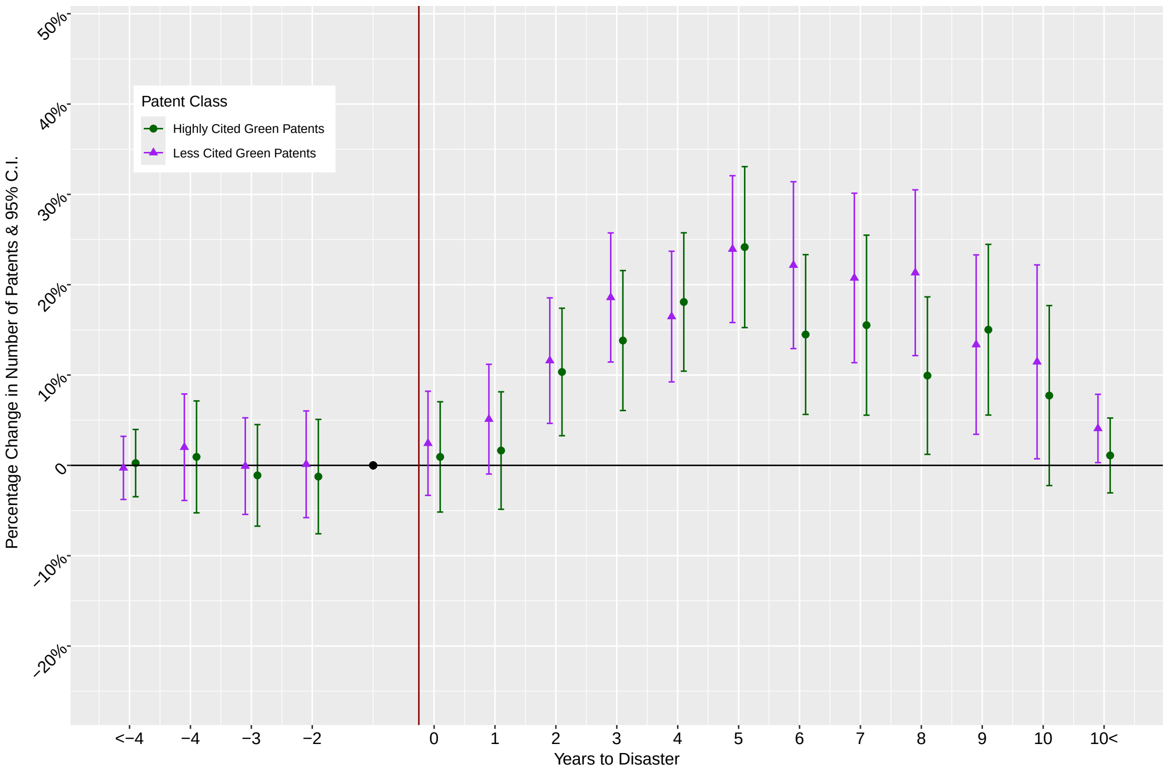

Figure 6: Patenting Activity following Natural Disaster Exposure by Citation

Note: This figure depicts the results for our baseline specification. We plot one regression for patents with citations above the median and one for patents with citations below the median. The sample average of highly cited green patents per year per region is 1.271, while sample average of less cited green patents is 1.253. Standard errors are clustered on the region level and confidence intervals are drawn for the 95% interval.

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. We therefore observe meaningful innovation in the wake of natural disasters.

Another commonly used way to measure patent value is for patents belonging to a triadic family. A triadic patent is a patent filed at the EPO, the JPO, and the 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 valued in some of the biggest markets on earth. We then use this indicator to estimate our event study for these triadic patents. Figure 7 plots our results.

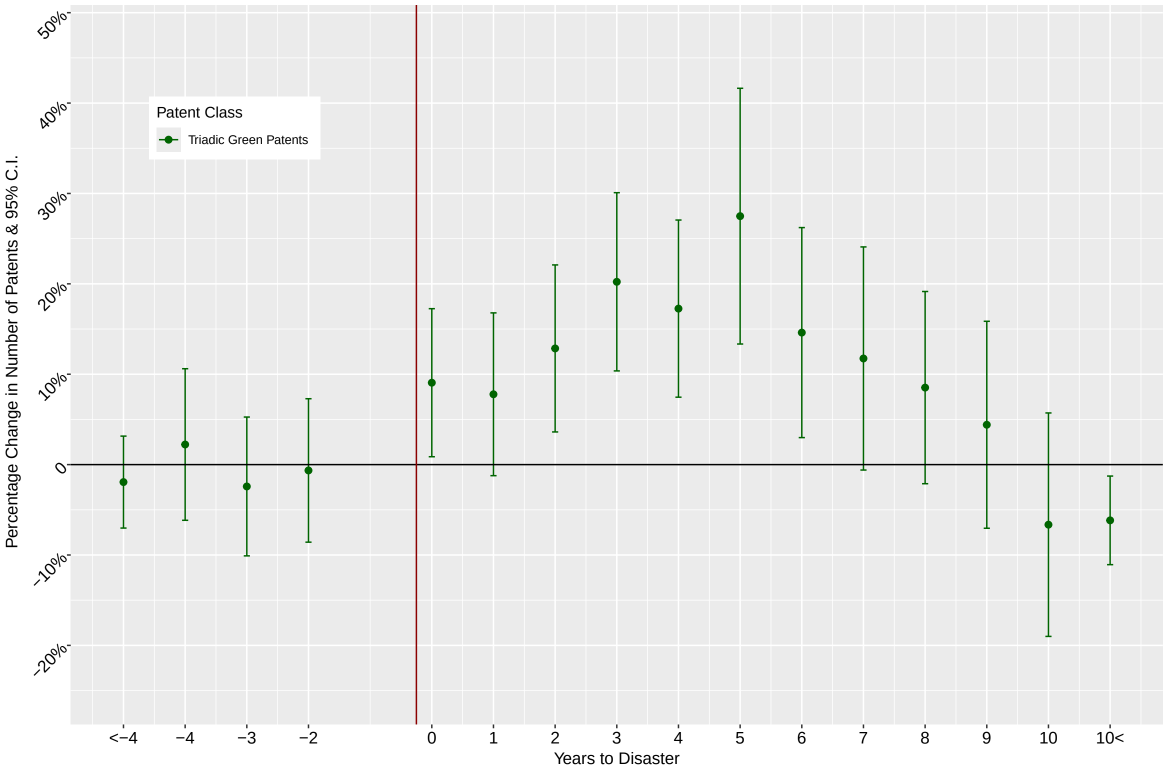

Figure 7: Triadic Patenting Activity following Natural Disaster exposure

Note: This figure depicts the results for our baseline specification. We restrict our sample to only include triadic green patents. The sample average of triadic green patents is 0.503. Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

We again find a similar pattern as in our baseline regression. We are, therefore, confident in stating that natural disaster exposure has a significant impact on the research and development of green technologies.

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 influences the examiner at the USPTO.

6.2 Alternative Measure of Green Innovation

Patent data are frequently used to measure innovation; however, the limitations of patents as an indicator are well-documented e.g. not all innovations are patentable, and not all firms opt to patent their innovations. To address this concern, we repeat our analysis using an alternative indicator for green innovation based on survey data from the Community Innovation Survey.

In general, the environmental part of the survey asks about two different types of green innovation. For our analysis, we develop three indicator variables related to green innovation: one for the introduction of new green products or services, another for the implementation of new green innovations within a firm, and an indicator for the introduction of any green innovation. This last dummy variable is assigned a value of one if the firm has introduced either a new green product or a new green innovation internally.

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 9: Effect of Natural Disasters on Self-Reported Green Innovation

	Dependent variable:		
	Green Innovation	Within-firm green innovation	Green Products
	(1)	(2)	(3)
Disaster Count Last 3 Years	0.0669***	0.0629***	0.0435***
	(0.0070)	(0.0068)	(0.0052)
Firm Size F.E. (employment)	Yes	Yes	Yes
Revenue	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Industry F.E. (2-digit NACE)	Yes	Yes	Yes
Observations	15,395	15,426	15,226
R^2	0.630	0.592	0.452
Adj. R^2	0.628	0.590	0.449

Note: "Disaster Count Last 3 Years" is the count of natural disasters in the past 3 years. Firm Size is a vector of dummies for a firm being small, medium or large dependent on the number of employees. Standard errors are clustered on the region (Kreis) level and are reported in parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

This analysis supports our prior findings and highlights the positive significant effect of natural disaster exposure on green innovation. In table 9, we regress all three indicators of green innovation on the count of natural disasters within the past three years. Our results corroborate the positive effect of natural disaster exposure on green innovation. Therefore, our findings are robust to alternative measures of green innovations. We do the same for the cumulative count of past natural disasters in Section A.5 of the appendix. Our results remain significant and qualitatively the same (magnitudes are smaller, since we regress a higher number of disasters on the same outcome).

6.3 Firm's Climate Affectedness

Another question is whether a firm's activities are actually influenced by the occurrence of natural disasters in its vicinity. To explore this relationship, we regress firms' perceptions regarding how extreme weather conditions have impacted their business on natural disaster exposure.

To analyze this effect, we rely on one survey question from the Community Innovation Survey conducted in 2021. Firms were asked, "During 2018 to 2020, how important were the following factors related to climate change for your business?" We created a dummy variable that equals one for the item "Impact of extreme weather conditions (e.g., disturbances in transport/logistics, damage from storms, flooding, drought)" if firms indicated that this factor had high, medium, or low importance.

Table 10: Effect of Natural Disasters on Firm's Self-Reported Affectedness

	Dependent variable:		
	Climate Affectedness		
	(1)	(2)	(3)
Disaster Count Last 3 Years	0.0879^{***} (0.0255)		
Disaster Count Last 10 Years		0.103^{***} (0.0125)	
Cumulative Count			0.0558^{***} (0.00691)
Firm Size F.E. (employment)	Yes	Yes	Yes
Revenue	Yes	Yes	Yes
Industry F.E. (2-digit NACE)	Yes	Yes	Yes
Observations	4,873	4,873	4,873
R^2	0.573	0.583	0.582
Adj. R^2	0.566	0.577	0.576

Note: Disaster count variables measure the impact of natural disasters over the last 3 years, last 10 years, and cumulatively. Firm Size is a vector of dummies for a firm being small, medium, or large depending on the number of employees. The analysis was conducted on data from one year. Standard errors are clustered on the region (Kreis) level and are reported in parentheses. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

Firms located in regions experiencing natural disasters are more likely to report being affected by climate change. This provides a robust "first stage," where natural disasters influence firms' perceived exposure to climate change (see Table 10).

6.4 Types of Inventors

We have previously shown that firms update their expectations about future green good demand and expect more stringent environmental regulation in the wake of a natural disaster. In this section, we investigate further what type of inventor responds to natural disaster exposure. PATSTAT allows us to distinguish between the types of inventors that are on a patent filing. This is possible, as PATSTAT not only contains the standardized names[19] for a patent's inventor and applicant, but also contains information on a patent applicant's sector, e.g., an applicant being a company or an individual.

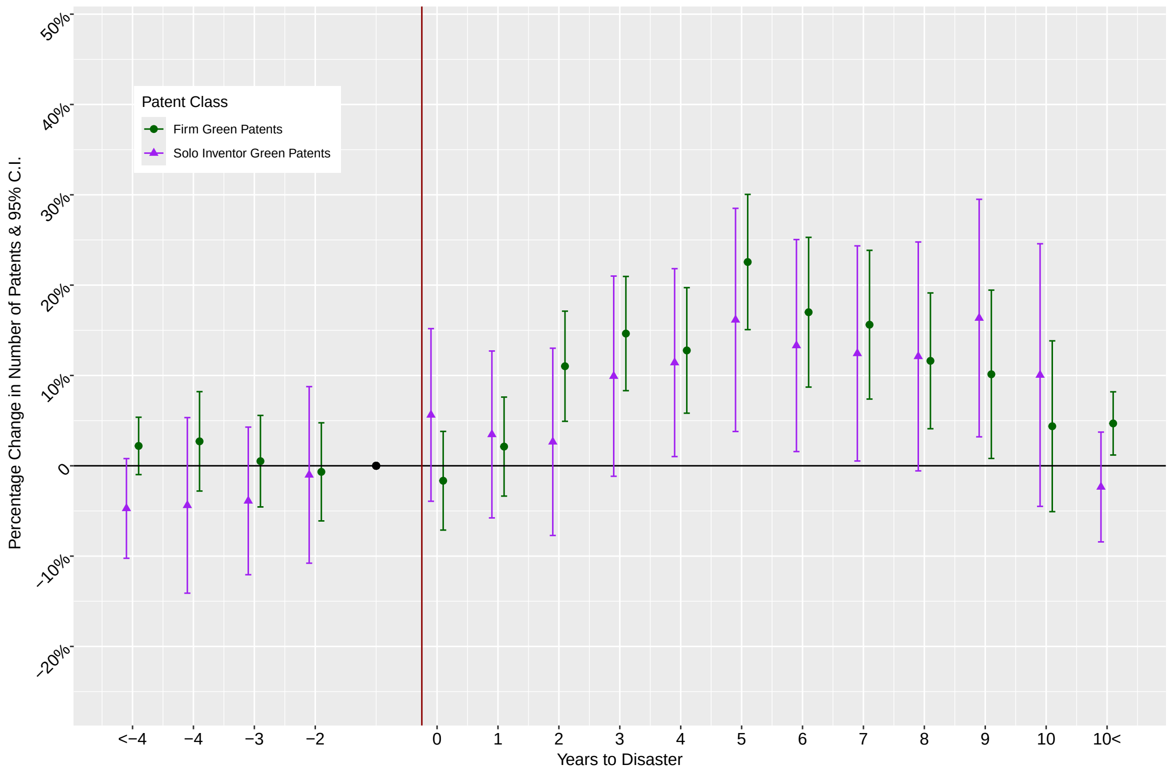

Figure 8: Patenting by Firms vs Individuals

Note: This figure depicts the results for our baseline specification when using our pooled country sample (France and Germany). We restrict our sample to patent filed by firms and patents filed by solo inventors. Standard errors are clustered on the region level and confidence intervals are drawn for the 95% interval.

We use the same regression as in equation (4), with our outcome variable now only summing over all patents filed by either companies or individuals. As patents can be filed by an individual and a company jointly, when focusing on individual patent holders, we only keep patents exclusively filed by individuals. Taking the example of firms, the comparison is then between firms exposed to natural disasters and firms

[19]For the standardization and sector assignment, PATSTAT uses data from ECOOM (K.U. LEUVEN).

not exposed to natural disasters. Figure 8 plots our preferred event-study specification. Both type of patent holders react to natural disaster exposure. As there are significantly more patents filed by companies, the estimates for companies are more precise.

6.5 Alternative Estimator

To account for the recent literature on heterogeneous treatment effects in difference-in-differences research designs, we use the estimator proposed in Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024). We then estimate our main results for green patents in figure 3 using their estimator and plot the results in figure 9. In our setting, this estimator compares the evolution of green patenting in regions with prior $(t-1)$ cumulative disaster exposure of, e.g., 2, that are exposed to an additional disaster at t, with those regions that also had a prior cumulative disaster exposure of 2 at $t-1$ but are not exposed at t. Regions drop out of the control group when they are treated (in our example setting, when their cumulative exposure amount switches from 2 to 3). The control group thus decreases the further away (time-wise) we are from $t-1$, as more and more units in the control group are exposed to a natural disaster. This estimator is, therefore, different from our preferred specification in equation (4), where the control group includes all regions and does not decrease (in terms of size) over time.

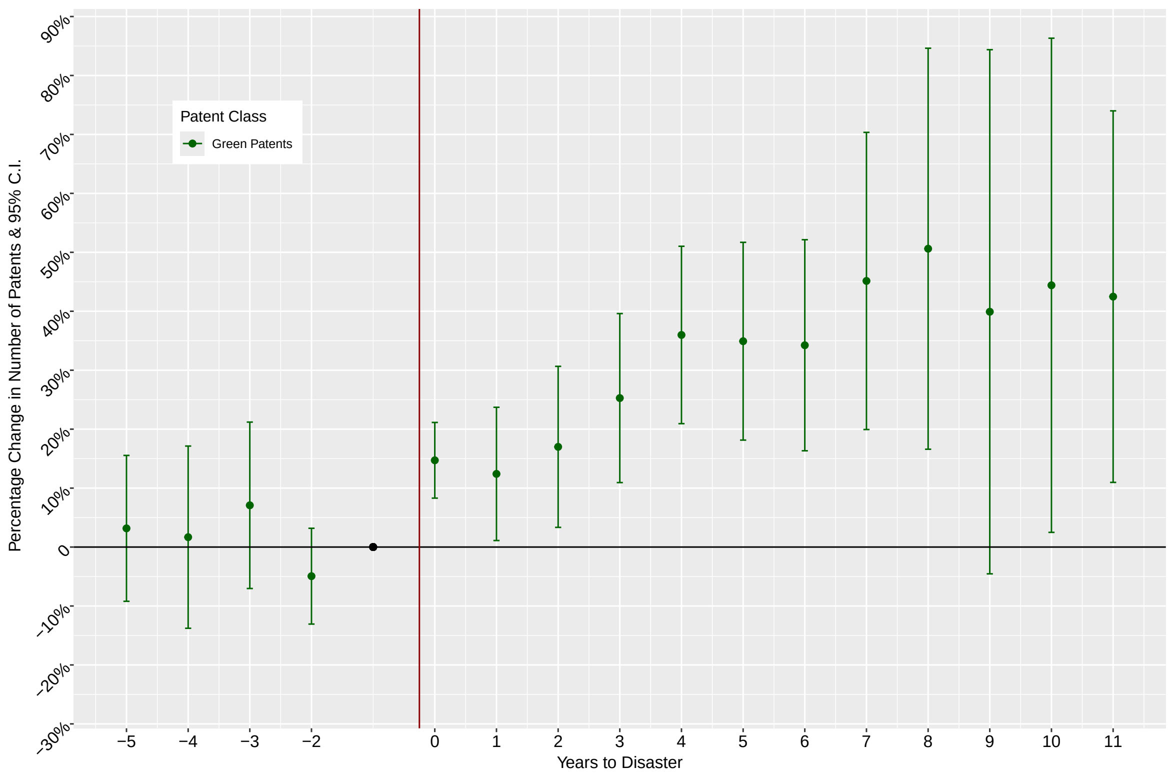

Figure 9: Patenting following the Exposure to a Natural Disaster - Estimator of Chaisemartin and D'Haultfœuille 2023; Chaisemartin and D'Haultfœuille 2024

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

Compared to our preferred specification, we find larger effects that do not decrease significantly over time. From our point of view, it is unclear which estimate is more precise, as our preferred specification is potentially more vulnerable to the peril of heterogeneous treatment effects, while the estimates plotted above have a very selected control group. It is, however, quite encouraging that we find significant and qualitatively similar results using the alternative estimator of Chaisemartin and D'Haultfœuille (2023) and Chaisemartin and D'Haultfœuille (2024), with our preferred specification being somewhat more conservative.

6.6 Disaster Severity

To further assess the robustness of our findings, we examine the effects of natural disasters across varying levels of severity in the appendix section A.6. While the most severe disasters exhibit slightly stronger impacts, the differences between the effects of severe and less severe events are not substantial. This suggests that our results are robust across a range of disaster intensities. It is worth noting that our dataset primarily includes severe natural disasters, limiting the representation of less intense events. Nonetheless, the consistent effects across the spectrum of severity provide confidence in the reliability of our conclusions. We split disasters based on the number of deaths, where severe disasters are those with deaths above the median value. We also present results for the most severe disaster a region has experienced, which leads to larger yet statistically more noisy coefficients.

7 Conclusion

This paper demonstrates that personal experience with natural disasters significantly increases green innovation, highlighting how external shocks influence inventors' behavior. The observed increase in green patenting is driven by shifts in inventors' higher-order beliefs—expecting greater demand for green goods and stricter environmental regulation. Notably, this effect is highly localized, with minimal spillovers, underscoring the importance of direct exposure in shaping innovation incentives.

Our results also highlight key market conditions that influence the responsiveness of inventors. Competition amplifies the effect of belief updates, suggesting that market structure plays a critical role in translating information shocks into technological progress. Similarly, larger green product markets foster stronger innovation responses, reinforcing the importance of consumer preferences in shaping inventive activity.

Beyond its theoretical contributions, our study has practical implications for climate policy. A well-functioning market for green innovation is crucial to ensuring that inventors act on new information about climate risks. The local nature of responses, however, points to inefficiencies—indicating that coordinated policies could enhance the global benefits of climate-related technological progress. Finally, by ruling out government research funding as a primary driver, our findings emphasize the role of private-sector incentives in shaping climate innovation.

An open question is whether inventors' responses are rational—that is, whether their expectations about the future align with actual outcomes. We intend to explore this further in future research.

References

Acemoglu, Daron (2002). "Directed Technical Change". In: *The Review of Economic Studies* 69.4, pp. 781–809. ISSN: 0034-6527.

— (2007). "Equilibrium Bias of Technology". In: *Econometrica* 75.5, pp. 1371–1409. ISSN: 1468-0262. DOI: 10.1111/j.1468-0262.2007.00797.x.

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous (2012). "The Environment and Directed Technical Change". In: *American Economic Review* 102.1, pp. 131–166. ISSN: 0002-8282. DOI: 10.1257/aer.102.1.131.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr (2016). "Transition to Clean Technology". In: *Journal of Political Economy* 124.1, pp. 52–104. ISSN: 0022-3808. DOI: 10.1086/684511.

Acemoglu, Daron and Joshua Linn (2004). "Market Size in Innovation: Theory and Evidence from the Pharmaceutical Industry*". In: *The Quarterly Journal of Economics* 119.3, pp. 1049–1090. ISSN: 0033-5533. DOI: 10.1162/0033553041502144.

Agatz, Niels, Yingjie Fan, and Daan Stam (2021). "The Impact of Green Labels on Time Slot Choice and Operational Sustainability". In: *Production and Operations Management* 30.7, pp. 2285–2303. ISSN: 1059-1478. DOI: 10.1111/poms.13368.

Aghion, Philippe, Roland Bénabou, Ralf Martin, and Alexandra Roulet (2023). "Environmental Preferences and Technological Choices: Is Market Competition Clean or Dirty?" In: *American Economic Review: Insights* 5.1, pp. 1–20. DOI: 10.1257/aeri.20210014.

Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt (2005). "Competition and Innovation: An Inverted-U Relationship". In: *The Quarterly Journal of Economics* 120.2, pp. 701–728.

Aghion, Philippe, Antoine Dechezleprêtre, David Hémous, Ralf Martin, and John Van Reenen (2016). "Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry". In: *Journal of Political Economy* 124.1, pp. 1–51. ISSN: 0022-3808. DOI: 10.1086/684581.

Aghion, Philippe and Peter Howitt (1992). "A Model of Growth Through Creative Destruction". In: *Econometrica* 60.2, pp. 323–351. ISSN: 0012-9682. DOI: 10.2307/2951599.

Bell, Alex, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen (2019). "Who Becomes an Inventor in America? The Importance of Exposure to Innovation*". In: *The Quarterly Journal of Economics* 134.2, pp. 647–713. ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjy028.

Bontadini, Filippo and Francesco Vona (2023). "Anatomy of Green Specialisation: Evidence from EU Production Data, 1995–2015". In: *Environmental and Resource Economics* 85.3, pp. 707–740. ISSN: 1573-1502. DOI: 10.1007/s10640-023-00781-7.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2022a). "Overreaction and Diagnostic Expectations in Macroeconomics". In: *Journal of Economic Perspectives* 36.3, pp. 223–244. ISSN: 0895-3309. DOI: 10.1257/jep.36.3.223.

— (2022b). "Salience". In: *Annual Review of Economics* 14.1, pp. 521–544. DOI: 10.1146/annurev-economics-051520-011616.

Bossle, Marilia Bonzanini, Marcia Dutra De Barcellos, Luciana Marques Vieira, and Loïc Sauvée (2016). "The drivers for adoption of eco-innovation". In: *Journal of Cleaner Production* 113, pp. 861–872. ISSN: 09596526. DOI: 10.1016/j.jclepro.2015.11.033.

Boustan, Leah Platt, Matthew E Kahn, and Paul W Rhode (2012). "Moving to Higher Ground: Migration Response to Natural Disasters in the Early Twentieth Century". In: *American Economic Review* 102.3, pp. 238–244. ISSN: 0002-8282. DOI: 10.1257/aer.102.3.238.

Calel, Raphael and Antoine Dechezleprêtre (2016). "Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market". In: *Review of Economics and Statistics* 98.1, pp. 173–191. ISSN: 0034-6535, 1530-9142. DOI: 10.1162/REST_a_00470.

Chae, Rebecca L., Rafay Siddiqui, and Yan Xu (2025). "Vulnerability to natural disasters and sustainable consumption: Unraveling political and regional differences". In: *Proceedings of the National Academy of Sciences* 122.5, e2409851122. DOI: 10.1073/pnas.2409851122.

Chaisemartin, Clément de and Xavier D'Haultfœuille (2024). *Difference-in-Differences Estimators of Intertemporal Treatment Effects*. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.3731856.

Chaisemartin, Clément de and Xavier D'Haultfœuille (2023). "Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: a survey". In: *The Econometrics Journal* 26.3, pp. C1–C30. ISSN: 1368-4221, 1368-423X. DOI: 10.1093/ectj/utac017.

Coibion, Olivier, Yuriy Gorodnichenko, Saten Kumar, and Jane Ryngaert (2021). "Do You Know that I Know that You Know...? Higher-Order Beliefs in Survey Data*". In: *The Quarterly Journal of Economics* 136.3, pp. 1387–1446. ISSN: 0033-5533. DOI: 10.1093/qje/qjab005.

CompNet (2022). *CompNet 2022, User Guide for the 9th Vinate of the CompNet Dataset*. Tech. rep.

De Rassenfosse, Gaétan, Jan Kozak, and Florian Seliger (2019). "Geocoding of worldwide patent data". In: *Scientific Data* 6. DOI: 10.1038/s41597-019-0264-6.

Dechezleprêtre, Antoine, Adrien Fabre, Tobias Kruse, Bluebery Planterose, Ana Sanchez Chico, and Stefanie Stantcheva (2022). *Fighting Climate Change: International Attitudes Toward Climate Policies*. Working Paper. DOI: 10.3386/w30265.

Dechezleprêtre, Antoine, Yann Ménière, and Myra Mohnen (2017). "International patent families: from application strategies to statistical indicators". In: *Scientometrics* 111.2, pp. 793–828. ISSN: 0138-9130, 1588-2861. DOI: 10.1007/s11192-017-2311-4.

Dernis, Hélène and Mosahid Khan (2004). *Triadic Patent Families Methodology*. OECD Science, Technology and Industry Working Papers 2004/02. DOI: 10.1787/443844125004.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt (2018). "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns". In: *American Economic Journal: Applied Economics* 10.2, pp. 202–233. ISSN: 1945-7782. DOI: 10.1257/app.20160307.

Djourelova, Milena, Ruben Durante, Elliot Motte, and Eleonora Patacchini (2024). "Experience, Narratives, and Climate Change Beliefs". In: *SSRN Electronic Journal*. ISSN: 1556-5068. DOI: 10.2139/ssrn.4680430.

Duckworth, Jay J., Mark Randle, Lauren S. McGale, Andrew Jones, Bob Doherty, Jason C. G. Halford, and Paul Christiansen (2022). "Do front-of-pack 'green labels' increase sustainable food choice and willingness-to-pay in U.K. consumers?" In: *Journal of Cleaner Production* 371, p. 133466. ISSN: 0959-6526. DOI: 10.1016/j.jclepro.2022.133466.

Feng, Josh, Xavier Jaravel, and Elias Einio (2021). "Social Push and the Direction of Innovation". In: *Academy of Management Proceedings* 2021.1, p. 10143. ISSN: 0065-0668, 2151-6561. DOI: 10.5465/AMBPP.2021.10143abstract.

Gallagher, Justin (2014). "Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States". In: *American Economic Journal: Applied Economics* 6.3, pp. 206–233. ISSN: 1945-7782.

Giuliano, Paola and Antonio Spilimbergo (2024). *Aggregate Shocks and the Formation of Preferences and Beliefs*. Working Paper 32669. National Bureau of Economic Research.

Guha-Sapir, Debarati, R. Below, and Ph. Hoyois (2022). *EM-DAT — The international disasters database*.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg (2005). "Market Value and Patent Citations". In: *The RAND Journal of Economics* 36.1, pp. 16–38. ISSN: 0741-6261.

Harhoff, Dietmar, Francis Narin, F. M. Scherer, and Katrin Vopel (1999). "Citation Frequency and the Value of Patented Inventions". In: *The Review of Economics and Statistics* 81.3, pp. 511–515. ISSN: 0034-6535. DOI: 10.1162/003465399558265.

Hassler, John, Per Krusell, and Conny Olovsson (2012). *Energy-Saving Technical Change*. Tech. rep. w18456. Cambridge, MA: National Bureau of Economic Research, w18456. DOI: 10.3386/w18456.

Hayek, F. A. (1945). "The Use of Knowledge in Society". In: *The American Economic Review* 35.4, pp. 519–530. ISSN: 0002-8282.

Horbach, Jens (2008). "Determinants of environmental innovation—New evidence from German panel data sources". In: *Research Policy* 37.1, pp. 163–173. ISSN: 00487333. DOI: 10.1016/j.respol.2007.08.006.

Horbach, Jens and Christian Rammer (2025). "Climate change affectedness and innovation in firms". In: *Research Policy* 54.1, p. 105122. ISSN: 00487333. DOI: 10.1016/j.respol.2024.105122.

Hornbeck, Richard and Daniel Keniston (2017). "Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872". In: *American Economic Review* 107.6, pp. 1365–1398. ISSN: 0002-8282. DOI: 10.1257/aer.20141707.

Hsiang, Solomon et al. (2017). "Estimating economic damage from climate change in the United States". In: *Science* 356.6345, pp. 1362–1369. DOI: 10.1126/science.aal4369.

Jaffe, Adam B. and Gaétan de Rassenfosse (2017). "Patent citation data in social science research: Overview and best practices". In: *Journal of the Association for Information Science and Technology* 68.6, pp. 1360–1374. ISSN: 2330-1643. DOI: 10.1002/asi.23731.

Kuchler, Theresa and Basit Zafar (2019). "Personal Experiences and Expectations about Aggregate Outcomes". In: *The Journal of Finance* 74.5, pp. 2491–2542. ISSN: 1540-6261. DOI: 10.1111/jofi.12819.

Laudenbach, Christine, Annika Weber, Rüdiger Weber, and Johannes Wohlfart (2023). *Beliefs About the Stock Market and Investment Choices: Evidence from a Survey and a Field Experiment*. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.3812346.

Malmendier, Ulrike and Stefan Nagel (2011). "Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?*". In: *The Quarterly Journal of Economics* 126.1, pp. 373–416. ISSN: 0033-5533. DOI: 10.1093/qje/qjq004.

— (2016). "Learning from Inflation Experiences *". In: *The Quarterly Journal of Economics* 131.1, pp. 53–87. ISSN: 1531-4650, 0033-5533. DOI: 10.1093/qje/qjv037.

McCrary, Justin (2007). "The Effect of Court-Ordered Hiring Quotas on the Composition and Quality of Police". In: *American Economic Review* 97.1, pp. 318–353. ISSN: 0002-8282. DOI: 10.1257/aer.97.1.318.

Miao, Qing and David Popp (2014). "Necessity as the mother of invention: Innovative responses to natural disasters". In: *Journal of Environmental Economics and Management* 68.2, pp. 280–295. ISSN: 00950696. DOI: 10.1016/j.jeem.2014.06.003.

Ministère de l'Enseignement supérieur, de la Recherche et de l'Innovation. (2023). *scanR — Search engine for French research and innovation exploration.*

Moscona, Jacob (2021). "Environmental Catastrophe and the Direction of Invention: Evidence from the American Dust Bowl". In: *SSRN Electronic Journal.* ISSN: 1556-5068. DOI: 10.2139/ssrn.3924408.

Moscona, Jacob and Karthik A Sastry (2023). "Does Directed Innovation Mitigate Climate Damage? Evidence from U.S. Agriculture*". In: *The Quarterly Journal of Economics* 138.2, pp. 637–701. ISSN: 0033-5533. DOI: 10.1093/qje/qjac039.

Nakamura, Emi, Jósef Sigurdsson, and Jón Steinsson (2022). "The Gift of Moving: Intergenerational Consequences of a Mobility Shock". In: *The Review of Economic Studies* 89.3, pp. 1557–1592. ISSN: 0034-6527, 1467-937X. DOI: 10.1093/restud/rdab062.

Osberghaus, Daniel and Carina Fugger (2022). "Natural disasters and climate change beliefs: The role of distance and prior beliefs". In: *Global Environmental Change* 74, p. 102515. ISSN: 09593780. DOI: 10.1016/j.gloenvcha.2022.102515.

Owen, Ann L., Emily Conover, Julio Videras, and Stephen Wu (2012). "Heat Waves, Droughts, and Preferences for Environmental Policy". In: *Journal of Policy Analysis and Management* 31.3, pp. 556–577. ISSN: 0276-8739.

Popp, David (2002). "Induced Innovation and Energy Prices". In: *American Economic Review* 92.1, pp. 160–180. ISSN: 0002-8282. DOI: 10.1257/000282802760015658.

Rassenfosse, Gaétan de and Bruno van Pottelsberghe de la Potterie (2009). "A policy insight into the R&D–patent relationship". In: *Research Policy* 38.5, pp. 779–792. ISSN: 0048-7333. DOI: 10.1016/j.respol.2008.12.013.

Rosvold, Elisabeth L. and Halvard Buhaug (2021). "GDIS, a global dataset of geocoded disaster locations". In: *Scientific Data* 8.1, p. 61. ISSN: 2052-4463. DOI: 10.1038/s41597-021-00846-6.

Schmidheiny, Kurt and Sebastian Siegloch (2023). "On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization". In: *Journal of Applied Econometrics* 38.5, pp. 695–713. ISSN: 1099-1255. DOI: 10.1002/jae.2971.

Sun, Liyang and Sarah Abraham (2021). "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects". In: *Journal of Econometrics* 225.2, pp. 175–199. ISSN: 03044076. DOI: 10.1016/j.jeconom.2020.09.006.

Trajtenberg, Manuel (1990). "A Penny for Your Quotes: Patent Citations and the Value of Innovations". In: *The RAND Journal of Economics* 21.1, pp. 172–187. ISSN: 0741-6261. DOI: 10.2307/2555502.

A Appendix

A.1 Subclasses of Y02

In figure 4 we pool all of the following classes into mitigation patents: Y02B "climate change mitigation technologies related to buildings, e.g. housing, house 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, i.e. information and communication technologies aiming at the reduction of their own 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", Y02T "climate change mitigation technologies related to transportation, and Y02W "climate change mitigation technologies related to wastewater treatment or waste managment".

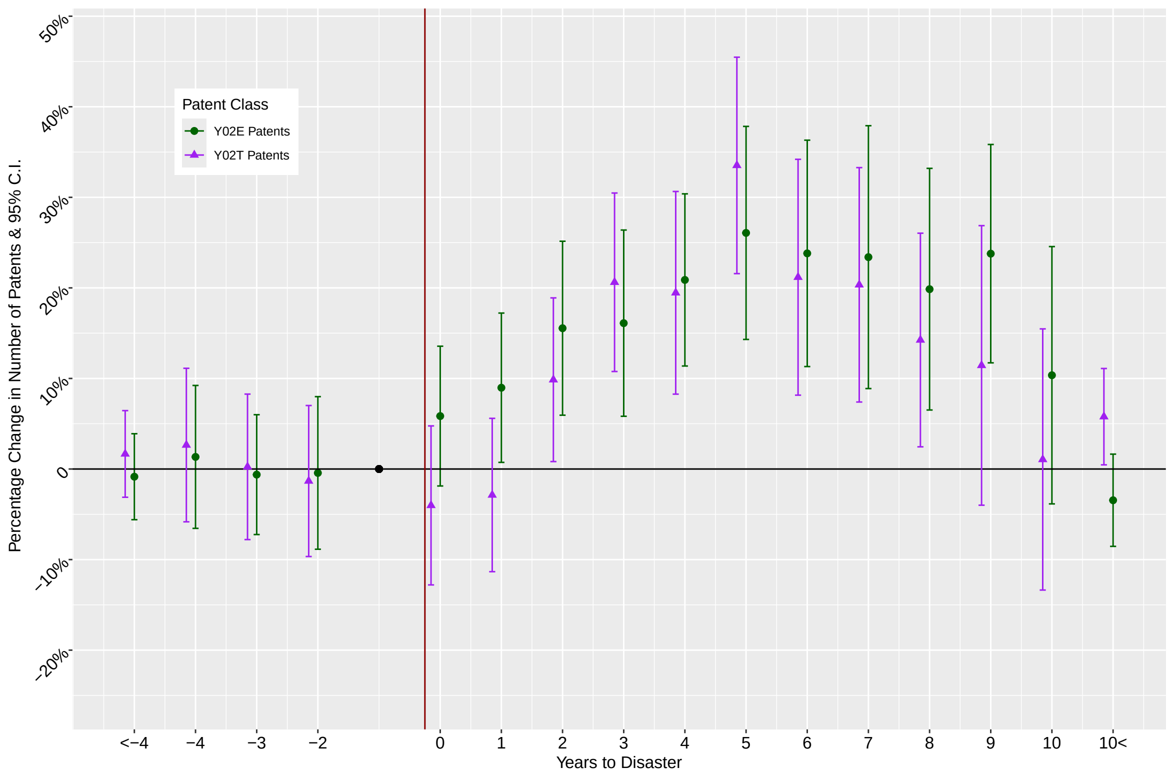

Figure 10: Patenting in the Y02E and Y02T subclasses

Note: This figure plots our baseline specification, when only looking at the Y02E and Y02T subclasses. Standard errors are clustered on the region level and confidence intervals are drawn for the 95% interval.

Table 11: Regression by Y02 subclass

	Dependent variable:							
	Y02A	Y02B	Y02C	Y02D	Y02E	Y02P	Y02T	Y02W
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disaster 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: In this table, we split the subclasses of Y02 and aggregate only the different subsamples to the separate regions. The respective sample means are reported below the table. 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

A.2 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:

$$z_{lj}(\Delta_j, E_l(\delta_j), \eta_j) = \frac{\Delta_j E_l\left[\pi_{Mj}\right]}{\kappa} = \frac{\Delta_j}{\kappa}\left(1 - \frac{1}{\Gamma(\eta_j)^{E_l[\delta_j]}}\right). \tag{34}$$

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 1: 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 $\frac{\partial^2 z_{lj}}{\partial \eta_j \partial E[\delta_j]} > 0$.

Hypothesis 3b: In addition to assumption 1, 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 should respond more strongly to increases in their expectation $E_l(\delta_j)$.

A.3 Alternative Green Good Window

This section plots the results, when we calculate the green good demand based on a 1 year and 3 year window respectively.

Table 12: 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:	0.0397**		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: Cumulative Count is the count of past natural disasters. 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 present year and the 2 years prior. Results are for our pooled country sample (France and Germany) 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 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 parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

A.4 Alternative Competition Windows

This section plots the results for alternative windows of competition that the inventors faced.

Table 13: 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)
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: *p<0.1; **p<0.05; ***p<0.01

A.5 Cumulative Disasters - Alternative Green Innovation Measure

	Dependent variable:		
	Green Innovation	Within-firm green innovation	Green Products
	(1)	(2)	(3)
Cumulative Count	0.0216***	0.0208***	0.0163***
	(0.00283)	(0.00287)	(0.00237)
Firm Size F.E. (employment)	Yes	Yes	Yes
Revenue	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Industry F.E. (2-digit NACE)	Yes	Yes	Yes
Observations	15,395	15,426	15,226
R^2	0.629	0.591	0.451
Adj. R^2	0.627	0.589	0.448

Note: Cumulative Count is the count of past natural disasters. Standard errors are clustered at the region (Kreis) level and are reported in parentheses. P-values: *p<0.1; **p<0.05; ***p<0.01.

A.6 Disaster Severity

The following figure plots our results when splitting disasters based on severity. The most severe disasters are those with deaths over the median value of deaths.

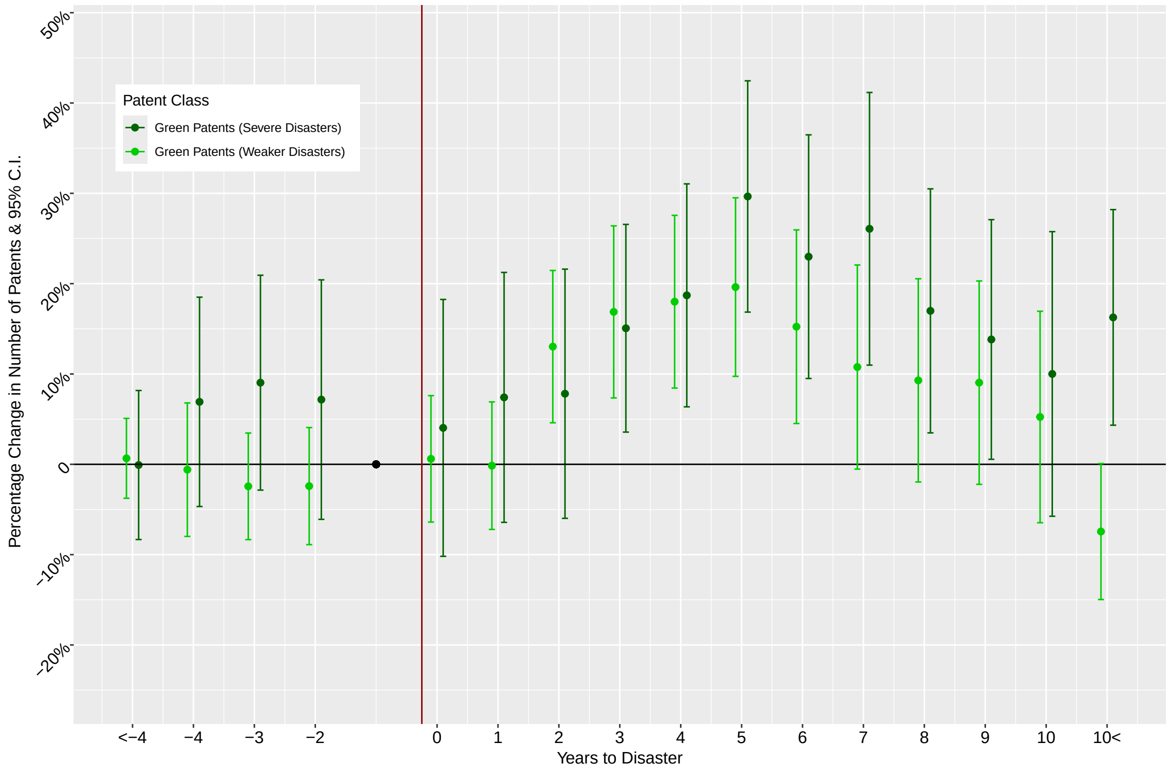

Figure 11: Patenting following above/below median disasters in terms of severity.
Note: Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

The following figure plots our results when only considering the most severe disaster a region has experienced. In this setting, all regions experience at most one natural disaster. We can thus use the estimator of Sun and Abraham (2021) to estimate this form of staggered adoption design. Once a region has experienced its most severe natural disaster, it remains "treated."

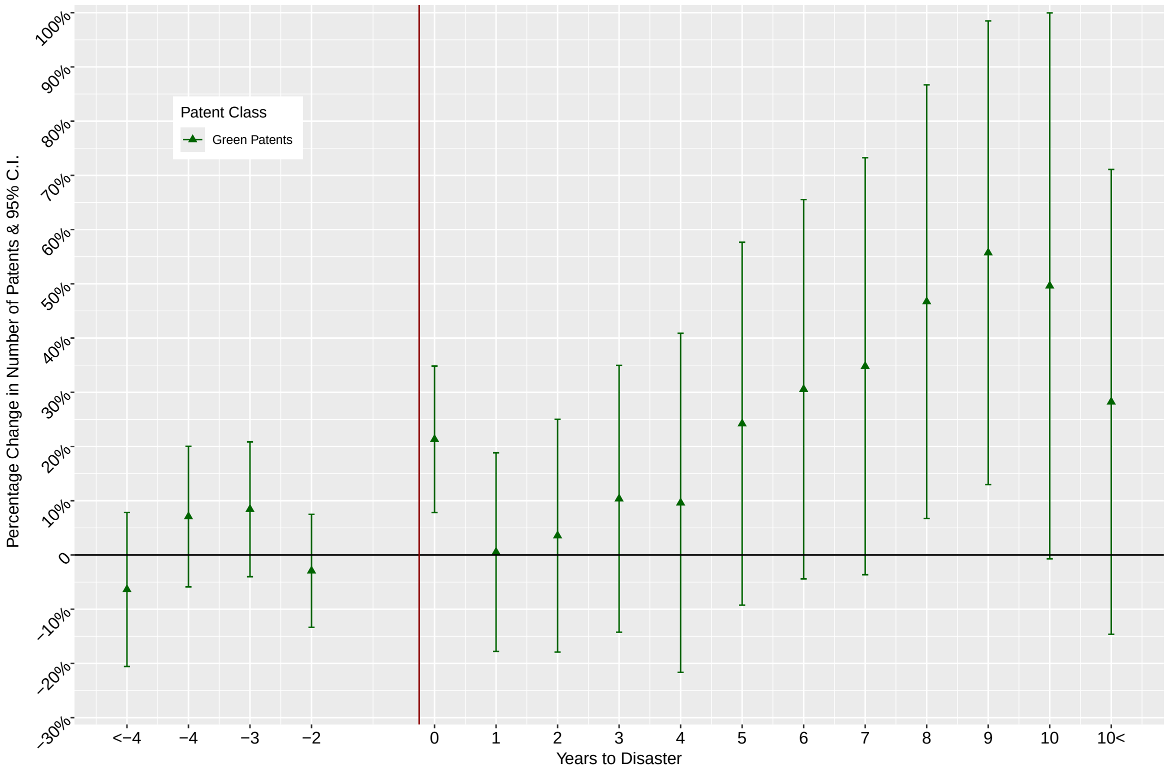

Figure 12: Patenting following the Exposure to the Most Severe Natural Disaster

Note: We use the estimator of Sun and Abraham (2021). Standard errors are clustered on the region level, and confidence intervals are drawn for the 95% interval.

A.7 Data

A.7.1 Countries in the CompNet Dataset

The following table depicts the time span for which different countries are available in the 9th vintage of the CompNet database. The information is directly taken from the CompNet website.

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 14: Comp Net TimpeSpans

A.7.2 Community Innovation Survey

For the construction of the variable describing the driving forces for the introduction of green innovation is based on the question "During [*the last two years*]], how important were the following factors in driving your enterprise's decisions to introduce innovations with environmental benefits?". Possible answers are Degree of importance "high", "medium", "low" and "not important".

Table 15: 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*

A.7.3 Table of Green Goods for PRODCOM

Table 16: Alternative Explanations

	Dependent variable:				
	Public Funding			Intrinsic Motivation	
	Dummy	Count	Budget	Voluntary Standard	Reputation
	(1)	(2)	(3)	(4)	(5)
Disaster Count Last 10 Years	0.00126 (0.00173)			0.00528*** (0.00196)	0.00140 (0.00323)
Cumulative Count		0.254 (0.385)	−1,224,154 (1,248,441)		
Year F.E.	Yes	Yes	Yes	Yes	Yes
Firm Size F.E.	Yes	No	No	Yes	Yes
Revenue	Yes	No	No	Yes	Yes
Industry F.E.	Yes	No	No	Yes	Yes
Region F.E.	No	Yes	Yes	No	No
CPC Controls	No	Yes	Yes	No	No
Observations	14,052	2,848	2,848	14,058	8,409
R^2	0.334	0.309	0.106	0.427	0.530
Adj. R^2	0.331	0.257	0.038	0.423	0.526

Note: "Disaster Count Last 10 Years" is the count of natural disasters in the past 10 years. Cumulative count is the count of past natural disasters. Regressions in column (1),(4) and (5) use German data from the Community Innovation Survey. Here, firm Size is a vector of dummies for a firm being small, medium or large dependent on the number of employees. Industry fixed effects are dummies for 2-digit NACE industries. Regressions in column (2) and (3) use French data from ScanR. Standard errors are clustered on the region (Kreis) level and are reported in parenthesis. P-values are as follows: *p<0.1; **p<0.05; ***p<0.01

Table 17: 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
32	26515255	Non-electronic flow meters (excluding supply meters, hydrometric paddlewheels)
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)

	PRODCOM Number	Label
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
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)

	PRODCOM Number	Label
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
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

	PRODCOM Number	Label
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
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...

	PRODCOM Number	Label
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
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

	PRODCOM Number	Label
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
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