Innovation as an Adaptive Response to Natural Disasters

- A Dynamic Cross-Country Panel Data Analysis of the Impact of Floods on Risk-mitigating Patents

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Abstract

As climate change is increasing the intensity and frequency of natural disasters worldwide, the question of coping with extreme events is gaining more attention. Within the climate discourse, innovation is an essential adaptation strategy. This study explores the relationship between natural disasters and risk-mitigating innovation by employing a dynamic cross-country panel data analysis on the impact of social and economic damage from floods on patent applications for flood-mitigating innovation domestically between 1996–2018. Inconsistent with prior literature and the theory of risk perception, the results provide no clear evidence of floods having a spurring effect on patenting activities. The estimated effects are significantly small for all damages, suggesting a weak positive impact on patents from economic damages, while social damage seems to have a slightly dampening effect. The findings contribute to the scarce research on the link between climate shocks and innovation as an endogenous process. Based on the findings of this study, more research is needed to improve the econometric approach and make further use of patent and damage data in order to examine how weather extremes influence proactive measures and adaptive responses.

Keywords: Climate Change Adaptation, Floods, Innovation, Natural Disasters, Patent, Risk Perception.

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Abbreviations and Definitions

EM-DAT	The International Disaster Database
EPO	European Patent Office
PATSTAT	Worldwide Patent Statistical Database
R&D	Research and Development
SQL	Structured Query Language
WIPO	World Intellectual Property Organization

Key Definitions

Adaptation:	Adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (IPCC, 2014).
Disaster:	A serious disruption of the normal functioning of a community or a society at any scale due to harmful events interacting with vulnerable social conditions, leading to one or more of the following: human, material and environmental losses and impacts (IPCC, 2014).
Mitigation:	An anthropogenic intervention to reduce the sources or enhance the sinks of greenhouse gases (IPCC, 2014).
Hazard:	A process, phenomenon or human activity that may cause loss of life, injury or other health impacts, property damage, social and economic disruption, or environmental degradation (IPCC, 2014).

1. Introduction

1.1 Background

Climate change and anthropogenic pressures are causing ecosystem degradation, biodiversity losses, and severe climate risks. An increase in the frequency and intensity of climate and weather extremes, including natural disasters such as floods, droughts, and fires, has led to widespread, pervasive impacts on ecosystems, humans, and infrastructure (IPCC, 2022). Extreme events are one of the main channels through which climate and socio-economic systems interact. As the number of extreme weather, climate, and water events are increasing and becoming more severe in many parts of the world, coping with natural disasters is gaining more and more attention (Botzen et al., 2019).

In the IPCC Sixth Assessment Report (IPCC, 2022), climate risk is defined as the potential for negative consequences for socio-ecological systems, recognizing the different values and objectives of such systems. These risks and their impact are generated by climate hazards, exposure, and vulnerability and are often expressed in terms of their damages, harms, and economic or non-economic losses. Hence, concepts such as hazards, vulnerability, adaptation, and resilience are central within the climate discourse. Providing a framework for understanding the interconnected consequences and impacts of climate change is essential for reducing adverse outcomes for current and future generations. Henceforth, recognizing climate risks can strengthen adaptation and mitigation actions that reduce these risks (IPCC, 2022).

Adaptation is a response to climate change's actual or expected effects, reducing climate risks and vulnerability by adjusting to existing climate systems and incorporating risk-mitigating strategies (IPCC, 2014). Important adaptation approaches to address climate change and reduce the risk of natural disasters are advances in research and development (R&D), technological innovations, and solutions. Thus, the link between weather shocks and innovative progress is a vital channel within the climate economy interface. However, this link is somewhat overlooked and understudied as an endogenous process. Instead, earlier literature has been looking more into the socio-economic consequences of climate change and the relation between weather extremes and economic performance. Indeed, innovation might be included as an indicator, although the direct endogenous effect on innovation has not been studied as much (Botzen et al., 2019).

Since technological innovation is one of the main tools with which we can deal with climate change, it is essential to understand the driving actors of green innovations and risk-mitigating technologies (IPCC, 2022). This study contributes to the research of what factor influences adaptive innovation by investigating the impact of floods on the advance of patent applications for risk-mitigating technologies on a domestic level over time**.** A dynamic panel-data regression analysis is employed to estimate the causal effect of reported social and economic damages from floods on the level of patents on technology for climate adaptation, minimizing the risk for and damage from floods. To carry out the analysis, panel data from 1996 to 2018 on filed patent applications from PATSTAT and damages from the EM-DAT database are used. As a set of country characteristics, data on national income, population density, total patents, and R&D expenditures are employed. In addition, country- and time-fixed effects are controlled for in the model, accounting for the heterogeneity present between countries and years in the panels.

1.2 Aim and Objectives

From the backdrop of the necessity of coping with and adapting to the severe outcomes of climate change outlined above, the overarching aim of this study is to further explore the relationship between natural disasters and technical innovation. The study sets out to assess the effects of natural disasters on patent applications by applying panel data on social and economic flood damages, along with risk-mitigating patent applications pertained to floods between 1996-2018. Studying the mechanism behind the adaptive responsiveness to damage from natural disasters, the theory of risk perception offers a conceptual framework positing that an increased perception of risk raises the demand for new technology and strategies for coping with risks. Based on the theoretical framework, this study examines whether experiencing a natural disaster updates peoples' perception of risk and increase the demand for adaptation measures.

2. Related Literature

The interest in the socio-economic impacts of climate change is extensive within the academic literature. Specifically in improving the estimates of the climate damage function, a simplified expression of the economic damages function of climate inputs needed when evaluating climate policies (see, e.g., Nordhaus, 2007; Botzen et al., 2019). Thus, the link between societal crises and socio-economic impacts is a common subject of interest that has been examined from several perspectives using different indicators for crises and economic performance. Previous studies have investigated the effects of financial crises, natural disasters, and climate extremes on socio-economic outcomes such as economic growth, fatalities, and the persistence of technical innovations.

A study by Felbermayr and Göschl (2014) examines the effects of multiple different natural disasters on economic activity by using data on the physical intensity of natural disasters. Their findings align with classical economic theory, indicating that natural disasters harm economic development in terms of GDP per capita progress. Although the magnitude of losses differs across countries, low- and middle-income countries experience the highest losses. However, another study by Cavallo et al. (2021) investigates the average causal impact of natural disasters on economic growth by combining results from different comparative case studies. Their results indicate that only two immense disasters harmed economic growth, mainly because of the radical political revolution that followed the disasters in those countries.

To investigate the causal link between temperature and economic production, a study by Kahlkul and Weinz (2020) empirically estimates historical climate impacts at different time scales. The authors use annual panels conducting long-difference and cross-sectional regressions for data of subnational economic output for a large set of regions in over 70 countries. Their findings indicate a non-linear impact on productivity levels from temperature; an increase in temperature in cold areas increases the economic output while reducing economic output in hot regions.

Kahn (2005) studies the relevance of economic dynamics when projecting the impacts of natural disasters by using data on annual deaths from natural disasters. The study tests several hypotheses regarding the relative importance of factors such as national income, geography, and institutions in protecting societies from climate shocks. Their results show that economic development has a dampening effect on the severity of the damage following climate shocks, demonstrating that economic development is an important factor in predicting disaster impacts. In addition, the results suggest that democracies, nations with higher-quality institutions and higher income equality suffer fewer deaths from natural disasters.

In contrast to these findings, Hallegatte (2012) studies the impact of economic development on the losses from natural catastrophes and concludes that economic progress increases the severity of damage from natural disasters. This increase in damage is because the natural hazard intensifies as the economy grows. Consequently, higher national income is arguably not always an answer to mitigating the disaster responses.

Nevertheless, it is essential to acknowledge that the impact on economic growth differs from the specific damage studied. On the one hand, the literature suggests that monetary damage increases with the infrastructure level as the exposure of capital increases. Still, on the other hand, societal damage such as deaths and human suffering are likely to decrease with economic development. Hence, wealthier countries tend to be more resilient than poorer ones, suffer fewer causalities and fatalities than poorer countries, but might still experience more considerable economic losses (Kahn, 2005; Hallegatte, 2012).

Another branch in the literature studies the impact of economic crises on the development of technical innovations, using patent data as a measure of innovation. One example is a study by Hardy and Sever (2021), who employ cross-country panel data on patenting at the industry level in the US. The study indicates a strong link between banking crises and economic growth channelled through innovation, claiming that financial crises are causing a decline in technological progress and innovation, which are argued to be important drivers of economic growth.

Surprisingly, the influence of natural disasters on innovation in an endogenous way is seldom studied, and its impact is still unclear. A search of the literature only revealed a few studies explicitly examining natural disasters' effect on innovations as an endogenous process, and their results are ambiguous.

Chen et al. (2021) study the influence of natural disasters on technical innovations from an economic point of view. They propose that natural disasters harm innovation by arguing that natural disasters bring severe consequences to the society, which might lead to a crowding out of R&D funding. Natural disasters are measured in the study by damage data on earthquakes, epidemics, extreme temperatures, floods, and storms. The analysis confirms the hypothesis that natural disasters reduce the general innovation level overall regardless of the type of disaster. However, the results indicate a somewhat heterogeneous effect on innovation from different natural disasters and their damage, with epidemics and deaths having the largest negative effect on innovation.

Miao and Popp (2014) examine innovative responses to natural disasters by positing innovation as an adaptive response to damage caused by disasters. Instead of using data on domestic patent applications like Chen et al. (2021), Miao and Popp (2014) measure innovation by patent application for specific technology aiming at minimizing the risk from natural disasters. They conduct a dynamic cross-country panel IV-regression for 28 countries covering 25 years (1970–2009), examining if different types of natural disasters influence behavioural change and the demand for adaptation tools and strategies. The results support the initial hypothesis that the number of patent applications in general increases with the severity of climate shocks, indicating that recent disasters stimulate domestic patenting activities.

When examining the responsive effects on patents of natural shocks, the kinds of patent applications used for measuring innovation seems to be of significance. On the one hand, Chen et al. (2021) use the total patent applications aggregated on a national level, exploring the impacts on the general innovative activities of a disaster chock. Chen et al. (2021) advocate that the close relation between innovative activities and economic performance implies that disasters have a negative impact on innovation activities. On the other hand, Miao and Popp (2015) measure patent applications for specific risk-mitigating technologies and expects a positive impact on innovation from natural disasters. Thus, seeing the creation of risk-mitigation technologies as an adaptive response to these shocks.

From the backdrop of the somewhat scarce and ambiguous results from prior studies within the field, this study further explores the relationship between natural disasters and technical innovation by assessing the effects of natural disasters on the patent applications for risk-mitigating technologies. This study is conducted through a dynamic panel data regression using data on 50 countries from 1996 to 2018. In contrast to prior studies, this study focuses on the impact of floods on patent applications, specifically for risk-mitigating technologies on floods. To the author's knowledge, this is the first study to undertake the extensive data on patents registered at the Worldwide Patent Statistical Database (PATSTAT), making use of the Cooperative Patent Classification. This classification accurately identifies patents related to a particular technology field and creates a more precise link between floods and risk-mitigating technologies related to floods.

3. Theory, Data and Empirical Method

This section starts with a presentation of the conceptual framework and model on which this study is based. Secondly, the data is presented, describing its sources, presenting the descriptive statistics, and discussing potential drawbacks or problems with the data. Thirdly, the econometric model employed when carrying out the analysis of the study is presented.

3.1 Theoretical Framework

3.1.1 Risk Perception

A common theory within protection motivation to examine risk management and community resilience is the theory of risk perception (e.g., Birkholz et al., 2014; Frondel et al., 2017; Mullis & Lippa, 1990). Risk perception is referred to intuitive judgements, through which people assess the potential impacts and consequences of a hazard and choose appropriate behavioural responses. The theory posits that an individual's risk perception is closely linked to self-protective behaviour, i.e., risk reduction behaviours and preparedness (Slovic, 1987; O'Connor et al., 1999). In recent years, the role perception plays in how individuals and communities respond to risk has gained widespread recognition in the contemporary risk management literature (Birkholz et al., 2014). The theory postulate that a disaster shock will raise the perceived risk of disaster incidences and increase the demand for adaptive technologies. With a growing demand for these technologies, the innovative sector is expected to become more motivated to develop new and more cost-effective technical solutions and technologies for mitigating future disaster risks (O'Connor et al., 1999).

Based on the methodology employed by Miao and Popp (2014), the perceived risk (R_{it}), which itself is unobserved, can be modelled as a function of prior disasters in a country, indicated by a distributed lag of the damage it caused (D_{it-1},.., D_{it-n}), the adaptive capacity (C_{it}), and domestic conditions, i.e., baseline hazard, in the country (H_i). The disaster damage is lagged in the model because technical innovations are characterized by systematic, non-linear, and dynamic processes. Thus, the adaptive response of these innovations will depend on the experience of damage in the past (IPCC, 2022). Hence, the model for the conceptual framework can be constructed formally in the following way.

$$R_{it} = f\ (\sum_{n=0}^{N} D_{it-n}\ , C_{it}, H_i) \qquad (1)$$

In equation (1), the modelling of perceived risk depends on disaster severity in terms of social and economic losses instead of the frequency or magnitude of the events. Because the disasters are measured in damage, the underlying simplified assumption for this setup is that the occurrence of disasters in a place where it causes no damage has no impact on people's risk perception and behaviour as they are not affected in a direct sense.

Drawing from the results from previous studies discussed in the literature review, various national characteristics can help explain the level of socio-economic impacts of natural disasters. Three factors that have been shown to play an important role in the expected capacity to adapt to natural disasters are national income, quality of institutions, and the general level of innovative activities (see, e.g., Kahn, 2005; Hallegatte, 2012). There are several ways to measure innovative activity. In the empirical model for this study, both innovative input and output are accounted for using the countries' yearly R&D expenditures and their total number of patent applications per year. Formally, the adaptive capacity, C_{it}, can be modelled as.

$$C_{it} = f(Y_{it}, I_{it}, K_{it-1}, P_{it}\ ) \qquad (2)$$

As such, adaptive capacity in country *i* in year *t* is a function of national income in country *i* in year *t*, (Y_{it}), institutional quality in country *i* in year *t* (I_{it}), the expenditures for R&D in country *i* in year *t-1* (K_{it-1}), and the total patents in country *i* in year *t* (P_{it}). One year lag is introduced in the model for the R&D expenditures because the outcome of these kinds of investments is expected to be delayed.

Hence, the risk-mitigating innovation (PAT_{it}) can be modelled as a function of the perceived risk (R_{it}) and adaptive capacity (C_{it}).

$$PAT_{it} = f(R_{it}, C_{it}) \tag{3}$$

It is worth mentioning that even though the theoretical framework posits that disaster damage has a spurring effect on innovations, the impact of these variables measuring adaptive capacity might be unclear. Higher institutional quality, GDP per capita, and R&D expenditures suggest an intensification of the adaptive capacity, which would lower the perceived risks and thus the demand for additional innovations. The effects of greater investments in innovative activities may thus move in different directions, either giving rise to more innovations or having a dampening effect on future breakthroughs (Miao & Popp, 2014).

3.2 Data

For the analysis of this study, panel data for 50 countries for the period 1996–2018 is collected, with patents of risk-mitigating innovations as the dependent variable and social and economic disaster impacts as the independent variables. In addition, covariates accounting for country-specific characteristics are included. In this section, the sources from which the data are collected are described in detail as well as a description of the sample selection for the panels.

3.2.1 Patent Data

A problem with examining adaptive innovation is that innovation is an abstract concept and hence difficult to measure. Given the important role innovation plays, e.g., for economic development, environmental policy, and adaptation in the climate economy interaction, it is necessary to find alternative ways to measure this factor. When measuring innovation, there is often a distinction between the process's input and output, which means that factors such as investments and expenditures into knowledge-creating processes are inputs to the innovative process. In contrast, factors such as new and cost-effective technical solutions are seen an outcome of innovation. Examples of indicators for measuring the input to innovation are R&D expenditures, cost improvements, learning rates, and the number of scientific personnel. A critic against using these kinds of data exclusively to measure innovation is that they only account for the input to innovation and do not reveal information on the innovative outcomes (Korres, 2012).

A common way to assess innovative activity, accounting for both inputs and outputs of the process, is to use patent data. A patent is an intellectual property related to inventions in the technical field. It can be granted to a firm, an individual, or a public body by a patent office. There are specific requirements that must be met by a patent application: the innovation needs to be novel, involve an inventive step, and be applied to the industry (Popp, 2019). According to Korres (2012), statistics on the patent application are preferable to statistics on patents granted when conducting international comparisons. Patent application data is preferred because of the time lag present between the date for applications and grants, which can be up to several years in some countries. Patents themselves are indicators of the output of innovation, but since they are recorded by date, they can also be seen as a partial indicator of R&D activity (Korres, 2012).

Patent data usually contains a comprehensive record with detailed classifications of each application available, convenient for distinguishing between different types of innovations. For this study, data on patent applications is extracted from the

European Patent Office's (EPO's) online database called PATSTAT. The database contains bibliographical and legal event patent data relating to more than 100 million patent documents from industrialized and developing countries. Patent applications based on specific characteristics or qualifications can be obtained through the web-based interface by running queries with SQL, a standardized programming language called Structured Query Language (SQL). PATSTAT also provides tools for making statistical analyses, visualizations, and downloading the data for offline use.

The dependent variable in the study is patent applications related to technologies for adaptation to climate change-associated with floods, classified Y02A 10/*. The "Y scheme" is a classification carried out by the European Patent Office for sustainable patents and provides separate categories for technologies relating to climate change mitigation and adaptation. The subclasses cover technologies for adapting to climate change, i.e., technologies that adapt to the adverse effects of climate change in human, industrial, and economic activities. The full description of the classification and the different subcategories is presented in Appendix A, and the specific query used for obtaining the desired patent application is presented in Appendix B. The patent data is aggregated at the country and year level by the application authority (i.e., receiving office) of the patent application and filing date. The applications are not only filed to domestic application authorities but also international offices such as the European Patent Office and the International Bureau of the World Intellectual Property Organization (WIPO). The patent applications filed to these international offices are excluded from the data set since these cannot be allocated to a country within this sample.

Figure 1 depicts the total sum of patent applications related to flood mitigation over time for the countries in the sample. As indicated in the figure, the number of patent applications increased remarkably after 2015. The trend is confirmed by Figure 2, presenting the share of flood patents out of the total patent for the sample during the period, reaching up to 0.04 per cent post-2015.

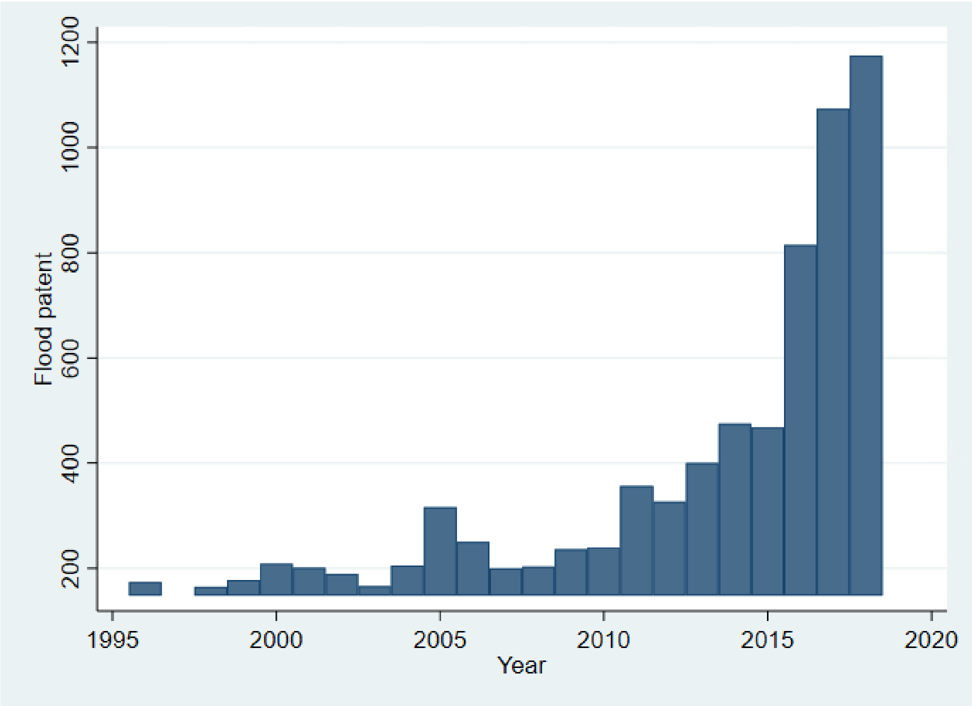

Figure 1. Sum of flood adaption patents between 1996–2018.

Note: Flood patent are in numbers as the sum of patents for all countries in the sample.

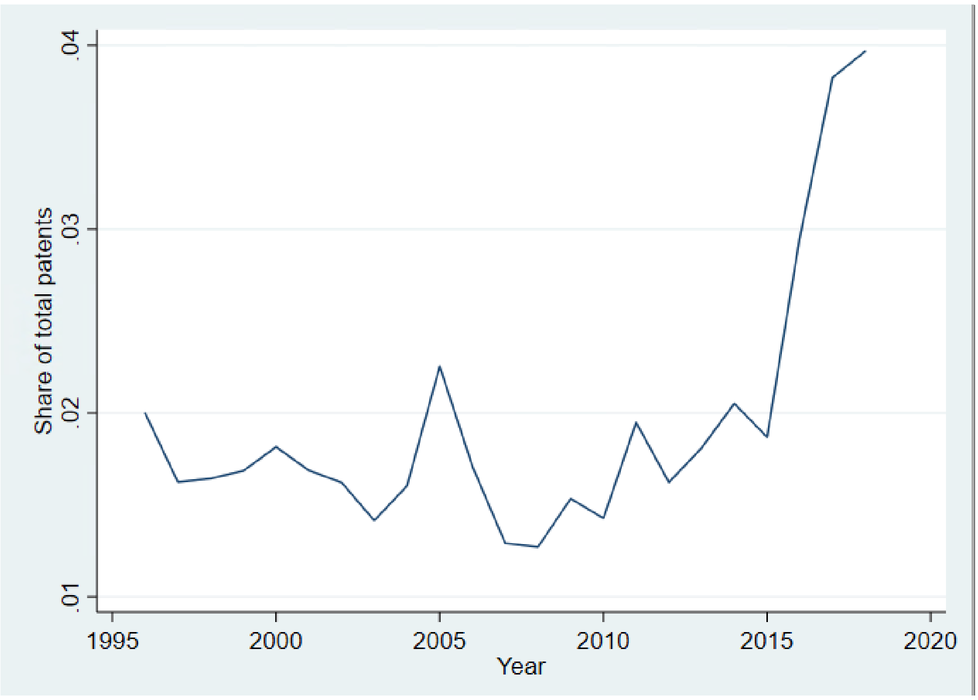

Figure 2. Share of flood patent applications for the period 1996–2018.

Note: The share of flood patent is in per cent and refers to the share of flood patents of the total number of patents for all countries in the sample.

3.2.2 Damage Data

The independent variables in this study are damage caused by natural disasters represented by data covering observations of disaster severity from flooding events. Consistent with prior studies, disaster data is retrieved from the Emergency Event Database (EM-DAT) provided by the Centre for Research on the Epidemiology of Disasters. EM-DAT is a publicly assessable database commonly used in cross-country studies when examining the effects of natural disasters. It covers essential core data on the occurrence and impact of over 22 000 mass disasters in the world starting from the 1900s. The data is compiled from various sources such as UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. The database differentiates between several disaster sub-types, starting with two main categories, natural or technical disasters, which are followed by several sub-types of catastrophes. To retrieve adequate data for flood damage, the damages are collected by selecting the following categories: natural disasters, hydrological, flood, coastal flood, and their related sub-types: riverine flood; flash flood; ice jam flood.

Besides information on the place and date of the disaster event, the EM-DAT database provides several measurements of disaster intensity, both in terms of human suffering and economic impacts. Based on the data coverage for the countries in the panel data, three of these damage measures are used as independent variables to comprehensively cover the main disaster impacts. Two of them account for the social damage in terms of the total amount of deaths and total affected. The third one measures the economic impact of floods as total estimated economic damage. Total deaths are the sum of deaths and missing people, and total affected is the number of people injured, affected, and homeless.[1] The estimated economic damage, referred to as total damage, is reported to the EM-DAT in current thousand

[1] The number of people who lost their lives because the event happened and the number of people whose whereabouts since the disaster are unknown and presumed dead based on official figures (EM-DAT)

US dollars at the time the flood occurred.[2] For consistency reason with other variables in the analysis, these values have been adjusted to million US dollars at 2017 constant prices.[3] For the damage to be reported to EM-DAT, the disaster event must have resulted in either ten or more deaths, over 100 people affected, or a filed declaration of a state of emergency or an appeal for international assistance.[4] Consequently, smaller flooding events not fulfilling these criteria are not reported.[5]

The development of flood damage is illustrated in Figures 3, 4, and 5 for total deaths, total affected, and total damages, respectively. These developments roughly demonstrate that economic damages seem to have increased in the recent years while total deaths and total affected have been declining over the same period.[6] Hence, implying that while the number of flood patents seems to increase, flood damage is somewhat declining.

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[2] A Consumer Price Index (CPI) has been used to convert the damages reported at the time the disaster occurred to the current US dollars value.

[3]For the adjustment, price level of CCON (PPP/XR) at the price level of USA GDP in 2017 from Penn World Table is used.

[4] Please see the EM-DAT guidelines: https://public.emdat.be/about

[5] One example is the case of Sweden, where there was no reported damage from floods between 1996-2018, even though Sweden has seen an increasing number of floods in recent years (OECD, 2013).

[6] 2013 is an exception for total deaths.

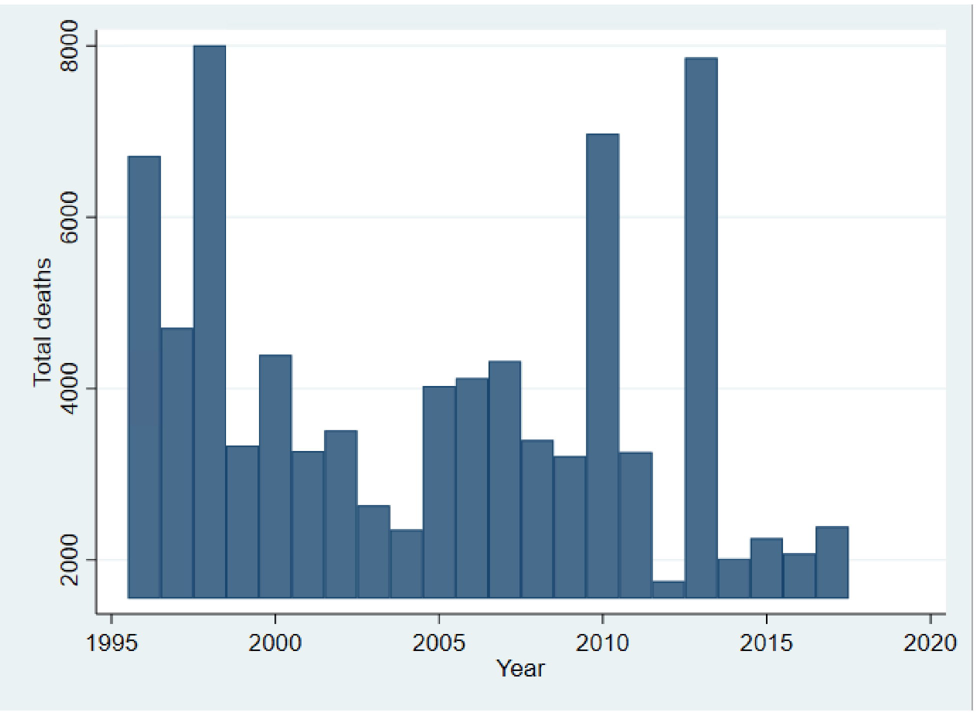

Figure 3. Sum of total deaths between 1996–2018.
Note: flood patents are in numbers and refer to the sum for all countries in the sample.

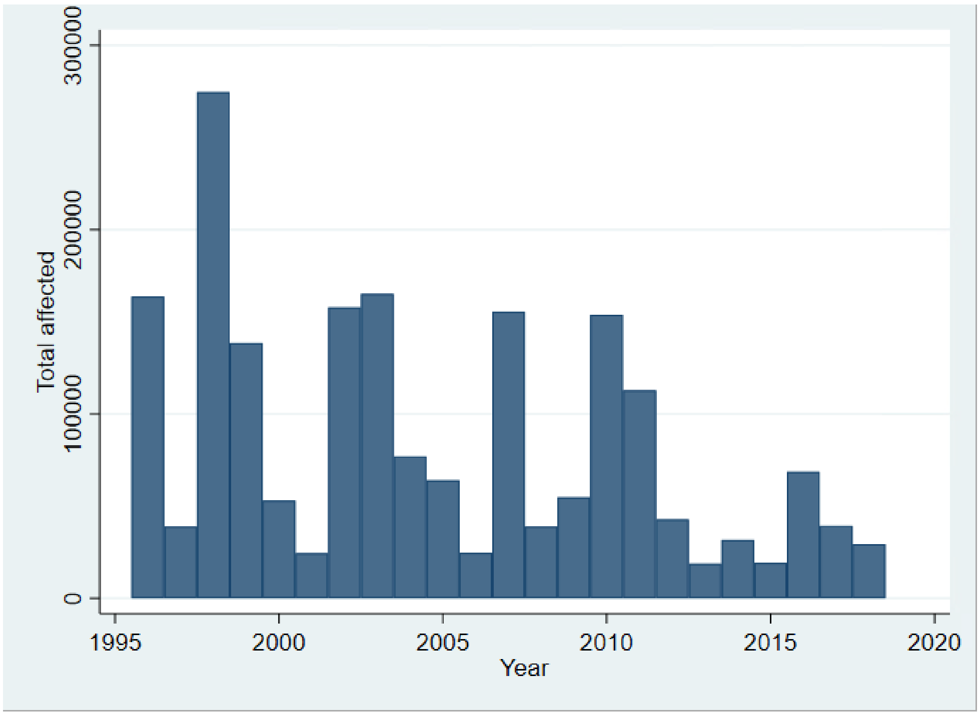

Figure 4. Sum of total affected between 1996–2018.
Note: total affected are in thousands and refer to the sum per year for all countries in the sample.

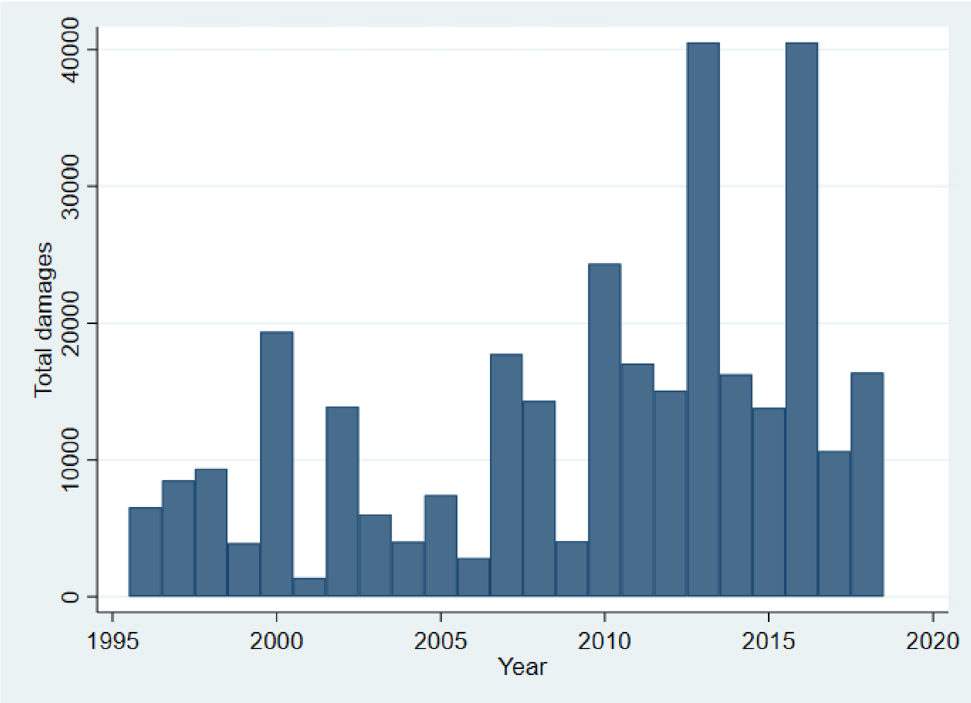

Figure 5. Sum of total damages between 1996–2018.

Note: total damages are in USD millions, 2017 constant prices, and refer to the sum of total damages for all countries in the sample.

3.2.3 Control Variables

To control for sample heterogeneity, which can help explain the domestic level of mitigation patents not spurred by flood damage, data on country characteristics are included in the data set. Data collected from Penn World Tables (PWT) on the real GDP in USD millions, 2017 constant prices, is used to measure a country's national income. These data are divided by the country's population (in millions) to obtain the country's real GDP per capita.[7] PWT is a database containing information on a wide range of characteristics, such as information on relative levels of income, outputs, inputs, and productivity levels, covering 183 countries between 1950 and 2019. Data on the countries' population density, R&D expenditures, and total patent applications are also included. Population density is measured as people per square kilometres of land area taken from the PWT. Data on the R&D expenditures (per

[7] Data on population is obtained from Penn World Tables.

cent of real GDP) is collected from the World Development Indicators from the World Bank. The total number of patents is obtained from WIPO.

3.2.4 Sample Selection

For the selected countries in the panel data used in this study, all countries included have at least one filed patent application within the Y02A 10/* classification and at least one reported damage in one of the three damage categories between 1996–2018. A detailed description of the mean patent counts, mean total deaths, mean total affected and mean total damages for the countries in the sample is presented in Table A3 in Appendix A.

Table 1 presents the descriptive statistics for all variables included in the data set. Notably, the number of flood patent applications is low compared to the values of reported damage, specifically concerning the social damage. Furthermore, there are fewer recordings for the variables institutional index and R&D expenditures because data is missing for some countries in some years. For R&D expenditures, data only covers observations for 1996–2018, hence the selected period for the study. Therefore, the panels are unbalanced in the iterated regressions for each damage measure. Observations are dropped when including institutional index and R&D expenditures in the last regressions (see Table C3–C5 in Appendix C). Still, these variables account for the adaptive- and initial innovative capacity and are thus essential for the estimation. However, the discrepancy between the coverage and size of data might lead to small coefficients in the estimations.

Taking a closer look at the sample distribution and the development of flood patents over time for each country, the sharp increase in total flood patent applications filed in China seems to be driving the overall post-2015 boost seen in Figure 1. The development of flood patents over time by country and the specific progress for China is presented in Figure C1 and C2, respectively, in Appendix C. The large number of flood patents filed in China compared to the other countries in the sample make the country an outlier in the data set and influence the estimations. Results from the estimations without China are presented in Table C2 in Appendix C. Despite having more scattered and less significant coefficients excluding China, the country's high data coverage speaks for the decision to include China in the final estimations.

Table 1. Descriptive statistics

Variables	Observations	Mean	Std. Dev	Min	Max
Flood patents	1,265	6.459289	46.2163	0	1 027
Total deaths (numbers)	1,265	69.6585	350.7984	0	6 453
Total affected (thousands)	1,265	1539.518	12379.3	0	242714.3
Total damages (millions)	1,265	252.4819	1245.743	0	19872.62
Other Variables					
Real GDP/Capita (millions)	1,265	24458.21	17027.78	2217.722	92922.88
Pop. Density (ppl/sq. km)	1,265	109.9307	105.7283	2.383531	511.7797
Institution index (-10 to 10)	1,209	7.257237	4.822769	-10	10
R&D expenditure (% of GDP)	1,209	1.114958	0.9003545	0.01524	4.95278
Total patents (thousands)	1,265	30.38532	114.9401	0	1459.255

Note: All monetary terms are adjusted to USD 2017 constant prices.

3.3 Empirical Method

Based on the theoretical framework constructed in section 3.1.1, a combination of the equations (1), (2), and (3) provides the following relationship.

$$PAT_{it} = f(\sum_{n=0}^{N} D_{it-n}, Y_{it}, I_{it}, K_{it-1}) \quad (4)$$

Then, a model for examining the relationship between floods and flood-mitigating innovations can be formulated as

$$PAT_{it} = f(\sum_{n=0}^{N} D_{it-n}, Y_{it}, K_{it-1}, I_{it}, P_{it}, X_{it}, u_i, \nu_t) \quad (5)$$

Hence, the dependent variable, innovation (PAT_{it}) is measured by the total number of patent applications for flood-impact mitigation in country *i*, in year *t*, as a function of past flood damage in country *i* in year *t-n* (D_{it-n}), national income in country *i*, in year *t* (Y_{it}), one year lagged R&D expenditures in country *i*, in year *t–1*, (K_{it-1}), institutional quality in country *i*, in year *t* (I_{it}), and the total patent applications in country *i*, in year *t*, (P_{it}).

In addition, population density (X_{it}) is controlled for which is expected to be an explanatory variable for a country's risk hazards over time. The model control for fixed effects for every country (u_i), and time fixed effects (ν_t). Country fixed effects accounts for the unobserved time-invariant heterogeneity across countries, such as the background hazards and culture, and time fixed effects control for factors specific for certain years common to all countries, such as financial crises or technical advancements affecting global markets.

Based on equation (3), the dynamic panel data regression can be modelled as.

$$PAT_{it} = \alpha + \beta D_{it-n} + \delta_1 Y_{it} + \delta_2 K_{it-1} + \delta_3 I_{it} + \delta_4 P_{it} + u_i + \nu_t + \varepsilon_{it} \quad (4)$$

Given the structure and characteristics of the panel data employed in this study, with count data as the dependent variable taking nonnegative integer values, commonly used models Poisson and Negative Binomial models. Poisson regressions are often used for modelling count data with nonnegative integers as they allow for observations taking the value zero. If applying an Ordinary least-square (OLS) regression with a log-transformed outcome variable, problems with data losses and undefined estimates would appear because log (0) is minus infinity (Correia et al., 2020). Nevertheless, the general Poisson model assumes the data to have a Poisson distribution, where the mean value equals the variance. Empirically, count data is often overdispersed, meaning there is a discrepancy between the mean and variance, where the variance is larger than the mean value. The patent data employed in this study also show signs of overdispersion as the variance is larger than the mean value.

A search through the literature has proposed two ways to solve the problem with overdispersion. One way to address the overdispersion in the model is to use a fixed-effects negative binomial (FE NegBin) approach as suggested by Hausman et al. (1984).[8] Another suggestion proposed within the literature is to use a fixed-effects Poisson (FEP) model with standard errors clustered at the country level, which will give robust results to any misspecification of the Poisson distribution and within-cluster correlation (Wooldridge, 1999). Given the critics against the NegBin model's accuracy in accounting for heterogeneity and following the prior similar study by Miao and Popp (2014), a fixed-effects Poisson (FEP) model is used for running the estimations.

Using a fixed-effects model is important because unobserved heterogeneity is likely to exist across the countries in the panel data to correlate with the covariates and influence the estimates. In addition, the regressions are also controlling for time-fixed effects, holding effects specifically for each year in the panel constant, such

[8] The FE NegBin approach allows the variance to be greater than the mean as the dispersion parameter provides a wider shape of the count data distribution.

as new beneficial international laws for patenting activities or similar, which might affect the patenting level.

4. Results

This section presents the results from the empirical estimation of the impacts of flood damage on innovation. As discussed in section 3.1.1., the FEP model is employed for the analysis, allowing for an interpretation of the patent counts as the dependent variable while still allowing for logarithmic transformations. Thus, the disaster damage coefficients can be interpreted as semi-elasticities, and the logs of GDP per capita, R&D expenditures, and total patents can be interpreted as elasticities.

The innovation response to flood damage is reported in Table 2 for total deaths, total affected, and total damages in columns (1)–(3), respectively. The individual coefficients of disaster damage lags (D t-1)–(D t-7) indicate the short-term impact, i.e., the yearly effect on innovation of an increase in disaster damage the year before. Seven years of distributed lags are selected following the method by Miao and Popp (2014), testing the sensitivity to lag length by gradually increasing the year lags and calculating the magnitude of the coefficients and standard errors. For total deaths, the coefficients generally become insignificant after four years lags, while the coefficients for total affected and total damages are insignificant beyond seven years. Thus, these results indicate that total affected and economic damage have a more persistent effect on innovation than fatalities. However, the same year lags for all three damages are used for consistency.

The coefficients are inconsistent across the year lags for the damage variables for the short-term impact of flood damage. For total deaths, the yearly effect shifts between being negative during the first four years and positive after six years.[9] The effect of total affected on patent counts is consistent across years as significantly negative, indicating a decrease of patents below minus 0.0001 per cent by an additional thousand affected. Contrary, the effect of total damages becomes

[9] Note that the positive effect is only significant at 10% significance level, hence less significant than the negative effects.

positively significant over time, mainly after a five- and six-year lag. Still, the estimated yearly effects are considered minor, with below 0.0001 per cent increase by an additional million dollars in economic damages.

However, analysing the coefficients for the cumulative effects, they also paint an ambiguous picture of the impact of flood damage. The long-term effects signal a small negative impact for social damage, deaths, and affected. More precisely, the coefficient for the cumulative effect of total deaths implies that one additional death decreases the patenting count by 0.011 per cent. An even smaller long-term effect is indicated by total affected, for which an additional thousand affected people decrease the patent count by 0.004 per cent. The equivalent coefficient for total damages indicates that an additional million dollars of monetary loss would spur the number of patent applications filed by 0.002 per cent. Thus, in line with the yearly effects, economic damages seem to be the only damage positively affecting patents in the long run.

The substantially small coefficients across all estimations suggest a rather neglectable effect that should not be overstated. As such, the analysis fails to find a substantial spurring impact of natural disasters on innovation, which is inconsistent with the theoretical framework of risk perception and the findings of prior literature. Possible reasons for this outcome will be discussed in the following section.

Table 2. Patent counts in response to flood damage.

VARIABLES	(1) Total deaths	(2) Total affected	(3) Total damages
D t	-0.000121**	-2.42e-06**	7.38e-06
	(5.49e-05)	(1.14e-06)	(9.52e-06)
D t-1	-0.000161**	-6.51e-06***	-1.14e-06
	(7.32e-05)	(1.48e-06)	(9.87e-06)
D t-2	-0.000302***	-8.19e-06***	1.72e-05*
	(6.98e-05)	(1.55e-06)	(9.79e-06)
D t-3	-0.000204***	-6.56e-06***	1.48e-05
	(3.83e-05)	(8.07e-07)	(1.40e-05)
D t-4	-0.000300***	-7.47e-06***	1.65e-05
	(3.55e-05)	(1.06e-06)	(1.39e-05)
D t-5	-6.71e-05	-5.03e-06***	3.66e-05***
	(4.40e-05)	(1.05e-06)	(1.20e-05)
D t-6	5.49e-05*	-1.62e-06***	5.07e-05***
	(2.84e-05)	(4.89e-07)	(7.30e-06)
D t-7	1.03e-05	-3.18e-06***	3.54e-05**
	(3.33e-05)	(1.09e-06)	(1.64e-05)
Cumulative effect	-0.0010893***	-0.000041***	0.0001775***
	(0.0003193)	(7.60e-06)	(0.0000481)
Log GDP/capita	2.463***	1.362*	2.344***
	(0.651)	(0.763)	(0.634)
Population density	0.00231	0.00402	0.00116
	(0.00724)	(0.00817)	(0.00808)
Institution index	-0.00133	-0.0360	0.0729*
	(0.0580)	(0.0429)	(0.0413)
Log R&D exp. t-1	-0.311	-0.283	-0.469
	(0.347)	(0.310)	(0.351)
Log total patents	0.843***	0.554***	0.548***
	(0.185)	(0.212)	(0.208)
Observations	704	704	704
Number of countries	50	50	50

*Note: All models include country and year fixed effects. Standard errors are clustered at the country level, presented in parenthesis; * p < 0.1, ** p < 0.05, *** p < 0.01*

5. Discussion

How to cope with threats of climate change and increasing disaster shock is an essential question for both policymakers and researchers to consider. In analysing the impact of flood damage on the number of risk-mitigating patent applications, the results provide no clear indications of natural disasters having a spurring effect on innovation. Several features of the study are important to note when discussing this outcome.

Firstly, it is not surprising to find fluctuation and inconsistency in the estimations of the yearly effects considering the nature of natural disasters and innovation. The occurrence of disaster shocks is inconsistent across years, and the impacts of a significant disaster can be much larger than those of several small events. Moreover, the innovative process is also less predictable, and patents may not be generated every year as an outcome of this process. Therefore, the cumulative impact of flood damages is more interesting from an analytical aspect. Societies are expected to be better equipped to respond and adapt to changes in the long run than in the short run. Thus, it is reasonable to believe that a cumulative increase in disasters would significantly impact innovations over time more than one single disaster in one year. In line with these predictions, the cumulative effect for the three damage variables is more consistent than the short-run effect. An interesting finding is that only economic damages indicate a spurring effect on patent applications, while the occurrence of social damage exhibits a negative influence.

These results can be partly explained by the plotting of the sample's damage. Relating to Figures 3, 4, and 5, provided in section 3.2.2, the general development of social and economic damages from floods is diverse; total deaths and total affected seem to have fluctuated over time but stagnated and decreased in recent years. On the contrary, the economic damages from floods have generally increased over time. These trends are in line with the results reported by Kahn (2005), discussed in section 2; economic development increases the resilience to disaster shocks and allows for more severe economic losses. Only countries with at least one patent application filed within the Y02A 10/* category are included in the sample selection. All countries within the sample thus have a somewhat operating patenting activity and can be considered to experience a general increasing trend of economic development. Hence, it is reasonable to expect the economic damages to roughly follow the same trend as the patenting activity confirmed by the estimations.

Secondly, as an explanation for the significantly low magnitude of the effects found, the estimated model might be suffering from omitted variable bias or simultaneously causality bias. Variation between the countries not absorbed by the fixed effects or influences on the extent of damage from the number of patents would introduce a negative bias of the coefficient towards zero and underestimate the impact of floods on innovation.

Thirdly, given the result of this study, there is no clear evidence of any adaptive responsiveness to floods. Rather, these results indicate that the occurrence of floods and the associated social and economic damages are not perfect in predicting the innovative response in this model. It could be the case that the close relationship between peoples' perception of risk and adaptive behaviour predicted is overestimated. Alternatively, the risk-mitigating patenting activity might fail to represent the adaptive responsiveness to floods. Perhaps people who experience a disaster shock are not responding by requesting new innovative adaptive technologies to the extent hypothesized, but rather existing solutions or techniques already accessible on the market. Moreover, regarding the cumulative effect for total affected, the coefficient is small and indicates an adverse effect on patents. An explanation for this could be that the adaptive response in many countries may be to move people away from hazardous areas or invest in more indirect solutions such as improving general infrastructure or inducing projects for poverty reduction. If this is the case, risk-mitigating patent applications will not be representative in reflecting the adaption or innovative reactions to floods. Such indirect responses to damage are not covered by the climate adaptation classification for which the patent data is collected.

Finally, not all innovations are patented due to protectionary reasons or because they do not fill the requirements by the patent offices. Also, the data on patent applications are assigned to a country based on application authority. A disaster in a country causing severe damage might spur domestic demand for risk-mitigating innovation but end up as a patent application in another country.

One suggestion to avoid this problem in future research is to estimate innovation in response to foreign shocks on a global level instead of on the country level, either grouping countries by continent or latitude. Categorizing countries by continent would also cover patent applications filed at international patent agencies.

5.1 Limitations

Despite the several advantages of using patent data to measure inventive activities, there are also significant drawbacks to consider. The level of patents is not linearly increasing with an increase in innovation, meaning there is not a perfect correspondence between these activities. Firstly, not all patents represent innovation, and not all inventions are patented. The relevance of patents for innovation differs where some patents are of little value to the innovative process while others are of considerable significance. Also, many inventions are deliberately not patented, e.g., for protectionary reasons (Nagaoka, 2010). Secondly, patents and their filing process are affected by the specific characteristics of each national patent system at a certain point in time. A problem specifically with using patent data in this study is the lack of recordings of the origin of the patent applicator. Instead, what is recorded in a balanced way for the patent applications are the residential receiving offices. Hence, the innovative response in one country can result in a patent being filed in another country for several institutional reasons. E.g., there are specific criteria that need to be fulfilled for an invention to be granted, and these criteria often change over time and differ between domestic patent offices. Consequently, it might be challenging to match these data with the actual inventive response and other economic data, such as disaster data in this study. In addition, patent applications covering the same or similar technical content can be filed at several offices simultaneously, meaning that the patents might not be unique (Nagaoka et al., 2010). These are feasible to identify through their patent family but require a more thorough data cleaning than the one conducted within the scope of this study.

The main concern with the study's empirical method is the threat to internal validity and the risk for endogeneity- and simultaneously causality bias. Even though country- and time-fixed effects are expected to absorb much of the sample heterogeneity, possible time-varying elements of a country's adaptive capacity could simultaneously affect the magnitude of damage from floods and innovation responses. In addition, simultaneous causality bias could appear in the model if there is a linear causal influence from the dependent variable to the independent variable and an influence on the independent from the dependent. Hence, if developed, wealthier countries with well-established institutions and patent offices would affect the impact of floods and the severity of flood damage, feedback effects could be introduced from the damage variables to the dependent variable and reversed.

The standard way for addressing problems with endogeneity and causality bias is to use an instrumental variable (IV) regression to estimate the causal effect of interest.[10] Miao and Popp (2014) acknowledge possible omitted variable bias in their model by introducing an IV approach with a measure of the physical magnitude for the different kinds of natural disasters they examine as the instrument.[11]

However, even though weather is a widely used instrument within social sciences, it has been criticized for not fulfilling the exclusion condition. Prior studies have shown that weather tends to predict additional effects on the variable of interest other than the one channelled through the independent variable.[12] For example, rain has been shown to explain economic outcomes endogenously (Mellon, 2021).

For this study, no IV approach has been applied. This is mainly because of the challenge of finding adequate data on flood intensity, such as data on storms, precipitation anomalies, and water levels at an aggregated level suitable to fit the panel data structure on countries and years. Because of the limitation in terms of time and resources, no such data has been feasible to apply in a way that would benefit the analysis.

[10] The theoretical motivation behind the IV approach is that an adequate instrument would isolate and capture movements in the dependent variable that is exogeneous, hence using this exogenous variation to estimate the causal effect (Stock and Watson, 2015).
[11] For floods, Miao and Popp (2014) control for the number of months in which precipitation exceeds 150 per cent of the long-term average monthly rainfall and the number of storms a country experiences in a given year. Geographical software is used for mapping the storms and calculating the frequency.
[12] For the IV approach to solve the problem with simultaneously causality bias; it needs to be exogenous, i.e., unrelated, to the error term, and it needs to be relevant, predicting the variation in the independent variable.

6. Conclusions

Climate change is intensifying and increasing the frequency of natural disasters worldwide. In order to gain insights into how to cope with and adapt to these threats, this study contributes to the research field by examining if the occurrence of floods induces the patenting level of risk-mitigating technology based on a theoretical framework of risk perception. While previous studies have mainly used data on total domestic patent applications or different search techniques with keywords to identify patents related to risk adaptation, this study is novel in using PATSTAT's extensive recordings on patent applications in the climate-adaptation category Y02A 10/*. In addition, to the author's knowledge, this study is the first attempt to analyse the relationship between floods and patenting activity globally after 2009. Hence, this study adds to the existing literature on the relationship between natural disasters and innovation examined in an endogenous way.

In contrast to findings from prior studies and the theory of risk perception, the results presented in this study fail to provide any consistent implications of floods having a spurring effect on patent applications. Only in the case of economic damages does there seems to be a small spurring effect on patenting activities in both the short- and long-run. In contrast, social damage seems to have a slightly negative effect over time. However, these results align with the development of damage reported for the sample. Economic damages have increased for the countries in the sample over time, while social damages have been declining. In addition, the significantly small size of the coefficients suggests that the estimated impact on innovation is rather negligible.

More research is needed to develop the econometrical approach to ensure higher internal validity and expand the reporting of patent data to examine what factors influence proactive measures to innovation and adaptive responses today. Essential improvements would be to find higher data coverage of the origin of the inventors of the patent applications and less limited measures on damage to get more accurate data on the impacts of disasters. Since innovation is a fundamental form of adaption, exploring how risk-mitigating innovations are initiated and spurred is essential to enable policymakers and the public sector to develop climate mitigation strategies for increased resilience to future climate risks.

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Appendix A. Patent Classification by EPO

Patent classification by the European Patent Office:

Classification symbol	Title and description
Y	General tagging of new technological developments; General tagging of cross-sectional technologies spanning over several sections of the IPC; Technical subjects covered by former USPC cross-reference art collections (XRACs) and Digests.
Y02	Technologies or applications for mitigation or adaption against climate
Y02A	Technologies for adaption to climate change
Y02A 10/00	… at coastal zones; at river basins
Y02A 10/11	Hard structures, e.g., dams, dykes, or breakwaters
Y02A 10/23	Dune restoration or creation; Cliff stabilization
Y02A 10/26	Artificial reefs or seaweed; Restoration or protection of coral reefs
Y02A 10/30	Flood prevention; Flood or storm water management, e.g., using flood barriers
Y02A 10/40	Controlling or monitoring, e.g., flood or hurricanes; Forecasting, e.g., risk assessment or mapping

Appendix B. Patent Search Queries

Patent search queries in PATSTAT:

```
SELECT *
FROM tls201_appln a join tls224_appln_cpc c ON c.appln_id = a.appln_id
left join tls202_appln_title on a.appln_id = tls202_appln_title.appln_id
WHERE (left (c.cpc_class_symbol,8) = 'Y02A 10' AND (appln_filing_year >=
'1990') AND (appln_filing_year < 9999))
ORDER BY appln_filing_date desc,  a.appln_id ,c.cpc_class_symbol
```

Appendix C. Additional Tables and Figures

Table C1. Sample statistics, mean patent counts, and damages for each country between 1996–2018.

Country	Patent	Total deaths	Total affected	Total damage
Algeria	0.1304348	62.13043	10.44209	16.78395
Argentina	0.5217391	8.391304	79.73448	137.7032
Australia	8.173913	5.782609	11.62565	659.0221
Austria	2.043478	3.782609	3.113739	164.54
Bosnia and Herz..	0.0434783	1.521739	57.81491	10.9843
Brazil	2.391304	130.7391	332.4037	172.6118
Bulgaria	0.2173913	3.565217	2.635522	13.75215
Canada	6	1.608696	8.434217	392.5682
Chile	0.3043478	13.78261	42.21526	49.41371
China	176.913	1162.13	61717.19	3890.287
Colombia	0.2608696	133.8261	456.4208	84.32231
Costa Rica	0.1304348	4.521739	22.10443	5.647873
Croatia	0.1304348	0.1304348	0.6716087	2.224118
Czech Republic	0.7391304	4.347826	70.53617	92.73499
Ecuador	0.173913	24.65217	27.10209	24.71752
Egypt	0.2608696	2.652174	0.2013043	0.0103319
El Salvador	0.0434783	5.652174	13.90787	19.83953
France	3.391304	8.304348	3.136957	387.0807
Georgia	0.173913	2.608696	6.692217	0.6754808
Germany	5.478261	2.565217	19.29165	1041.532
Greece	0.4347826	2.565217	0.8762609	22.9545
Guatemala	0.0434783	36.3913	47.64235	10.11678
Hungary	0.5652174	0.4347826	10.38543	16.16383
India	0.3478261	1449.391	18993.99	564.1713
Indonesia	0.0869565	234.8696	297.4597	93.07359
Israel	0.6086957	1.26087	0.0434783	1.296933
Italy	1.26087	15.13043	3.611217	385.6519
Japan	75.43478	30.95652	92.05396	1035.31
Malaysia	0.5217391	9.73913	35.54226	23.55912
Mexico	1.913043	78.13043	178.7271	93.51945
Morocco	0.4347826	15.6087	8.473739	3.816674
Netherlands	2.347826	0	0.0869565	17.31233
New Zealand	1.608696	0.2173913	0.4826087	30.57231
Norway	1.347826	0	0.0913043	0
Panama	0.0434783	4.217391	6.285522	0.3751793
Peru	0.3913043	63.43478	217.5334	77.02544

Philippines	0.5217391	144.8261	1122.907	46.11455
Poland	2.347826	5	15.05448	129.7719
Portugal	1.130435	2.73913	0.1875652	46.62343
Romania	0.3913043	14.08696	16.4533	48.07458
Russian Fed.	8.217391	29.6087	65.84452	55.02182
Saudi Arabia	0.0434783	17.43478	1.132565	20.12649
Serbia	0.173913	2.521739	3.998522	40.41622
Slovakia	0.173913	2.826087	2.130217	2.972023
Slovenia	0.173913	0.1304348	0.6326087	8.684375
South Africa	1.26087	15.13043	21.02917	24.34515
Spain	3.478261	7.130435	0.6336522	61.65071
Switzerland	0.4782609	2.608696	0.3209565	186.7572
Tunisia	0.1304348	2.521739	2.761217	0.4624711
Turkey	0.3913043	18.30435	61.27926	35.49567
Ukraine	0.2173913	3.391304	26.77191	16.20745
United Kingdom	5.652174	1.826087	18.8897	1044.813
US	35.52174	35.3913	525.8406	2323.835
Uruguay	0.0434783	0.6086957	8.633478	1.282812
Total	6.578905	70.94686	1568.027	252.481

Note: Total deaths are in people killed, total affected are in thousands and total economic damages are in million USD 2017 constant prices.

Figure C 1. Total sum of flood patent for 1996–2018 for each country in the sample.

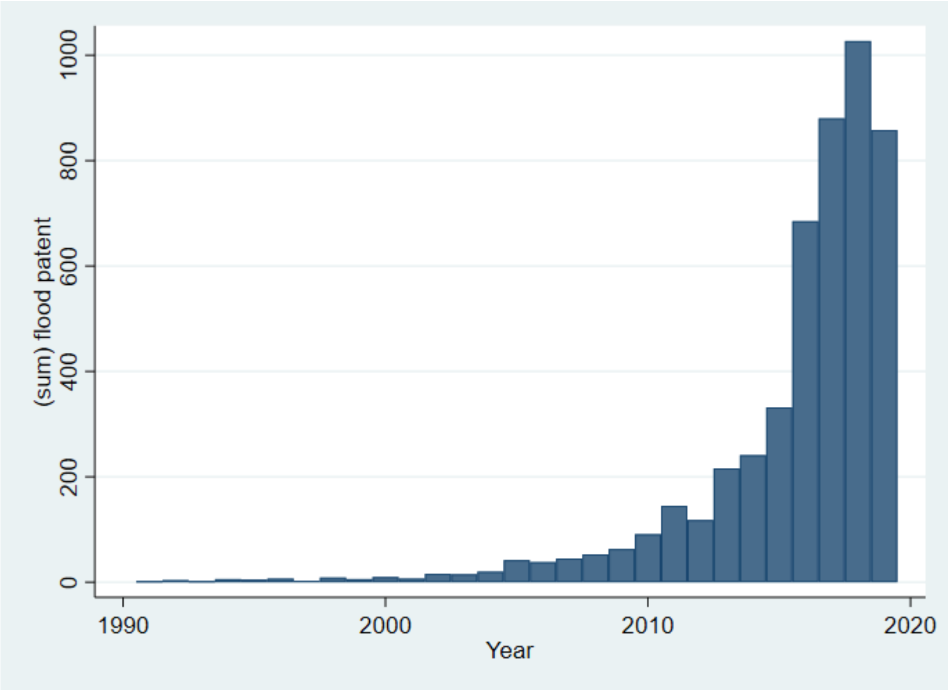

Figure C 2. Total sum of flood patents between 1996–2018 for China.
Note: flood patents are in numbers.

Table C2. Patent counts in response to flood damages not including China.

VARIABLES	(1) Total deaths	(2) Total affected	(3) Total damages
D t	-0.000181	7.84e-06	7.93e-06
	(0.000437)	(8.88e-06)	(8.87e-06)
D t-1	0.000251**	-3.89e-05***	8.11e-06
	(0.000101)	(8.42e-06)	(1.07e-05)
D t-2	-0.000574*	-3.25e-05***	7.40e-06
	(0.000345)	(1.17e-05)	(1.01e-05)
D t-3	-0.000337	-3.55e-05**	-1.64e-05
	(0.000209)	(1.52e-05)	(1.99e-05)
D t-4	-6.26e-05	-2.05e-05	-1.53e-05
	(0.000168)	(1.82e-05)	(9.93e-06)
D t-5	8.63e-05	-5.18e-06	-1.69e-05
	(0.000193)	(9.98e-06)	(1.52e-05)
D t-6	-4.40e-05	-2.51e-06	-7.49e-06
	(0.000299)	(9.62e-06)	(1.19e-05)
D t-7	-0.000453	1.24e-05	1.24e-05
	(0.000462)	(1.48e-05)	(2.14e-05)
Cumulative effect	-0.0013143	-0.0001149**	-0.0000202
	(0.0013236)	(0.0000445)	(0.0000499)
Log GDP/capita	1.769***	1.752**	1.949***
	(0.651)	(0.698)	(0.680)
Population density	0.00568	0.00647	0.00887
	(0.00918)	(0.00974)	(0.00926)
Institutional index	-0.0788	-0.0590	-0.0560
	(0.0733)	(0.0647)	(0.0636)
Log R&D exp t-1	-0.397	-0.336	-0.498
	(0.334)	(0.324)	(0.354)
Log total patents	0.121	0.133	0.267
	(0.179)	(0.194)	(0.239)
Observations	688	688	688
Number of countries	49	49	49

*Note: All models include country and year fixed effects. Standard errors are clustered at the country level, presented in parenthesis; * p < 0.1, ** p < 0.05, *** p < 0.01.*

Table C3*: Patent counts in response to total deaths.*

VARIABLES	(1) patent	(2) patent	(3) patent	(4) patent	(5) patent	(6) patent
Total deaths t	-0.000509***	-0.000241***	-0.000236***	-0.000235***	-0.000217***	-0.000121**
	(4.87e-05)	(4.86e-05)	(4.70e-05)	(4.86e-05)	(5.00e-05)	(5.49e-05)
Total deaths t-1	-0.000401***	-0.000247***	-0.000243***	-0.000242***	-0.000221***	-0.000161**
	(6.62e-05)	(7.07e-05)	(6.83e-05)	(6.96e-05)	(7.44e-05)	(7.32e-05)
Total deaths t-2	-0.000562***	-0.000344***	-0.000341***	-0.000340***	-0.000333***	-0.000302***
	(7.67e-05)	(7.17e-05)	(7.01e-05)	(7.26e-05)	(7.21e-05)	(6.98e-05)
Total deaths t-3	-0.000304***	-0.000244***	-0.000242***	-0.000241***	-0.000236***	-0.000204***
	(2.50e-05)	(3.50e-05)	(3.44e-05)	(3.86e-05)	(3.65e-05)	(3.83e-05)
Total deaths t-4	-0.000303***	-0.000346***	-0.000343***	-0.000342***	-0.000344***	-0.000300***
	(2.28e-05)	(3.54e-05)	(3.61e-05)	(3.88e-05)	(3.64e-05)	(3.55e-05)
Total deaths t-5	-0.000177***	-8.98e-05*	-8.97e-05*	-8.88e-05*	-8.66e-05*	-6.71e-05
	(3.18e-05)	(4.97e-05)	(4.92e-05)	(5.20e-05)	(5.16e-05)	(4.40e-05)
Total deaths t-6	-6.66e-05*	6.44e-05**	6.49e-05**	6.62e-05**	6.73e-05**	5.49e-05*
	(3.92e-05)	(3.22e-05)	(3.18e-05)	(3.12e-05)	(3.09e-05)	(2.84e-05)
Total deaths t-7	-0.000187***	3.89e-06	3.25e-06	3.89e-06	9.86e-06	1.03e-05
	(2.99e-05)	(3.93e-05)	(3.89e-05)	(3.87e-05)	(3.79e-05)	(3.33e-05)
Cumulative effect	-0.00251***	-0.0014432***	-0.0014271***	-0.0014194***	-0.0013599***	-0.0010893***
	(0.0002149)	(0.0003179)	(0.0003099)	(0.0003222)	(0.0003212)	(0.0003193)
Log GDP/capita		5.494***	5.399***	5.390***	4.981***	2.463***
		(0.190)	(0.230)	(0.253)	(0.407)	(0.651)
Population density			0.00856	0.00891	0.0134	0.00231
			(0.00866)	(0.00878)	(0.00928)	(0.00724)
Institutional index				0.00986	0.0250	-0.00133
				(0.0932)	(0.0838)	(0.0580)
Log R&D exp t-1					0.528	-0.311
					(0.424)	(0.347)
Log Total patents						0.843***
						(0.185)
Observations	832	832	832	797	705	704
No. of countries	52	52	52	50	50	50

Note: Total deaths are in numbers. All models include country and year fixed effects. Standard errors are clustered at the country level, presented in parenthesis.

** p < 0.1, ** p < 0.05, *** p < 0.01*

Table C4*: Patent counts in response to total affected.*

VARIABLES	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent	(6) Patent
Total affected t	-6.48e-06***	-4.02e-06***	-3.92e-06***	-3.96e-06***	-3.74e-06***	-2.42e-06**
	(8.75e-07)	(9.69e-07)	(9.14e-07)	(9.12e-07)	(9.90e-07)	(1.14e-06)
Total affected t-1	-1.26e-05***	-8.01e-06***	-7.96e-06***	-8.07e-06***	-7.61e-06***	-6.51e-06***
	(8.51e-07)	(1.31e-06)	(1.27e-06)	(1.31e-06)	(1.38e-06)	(1.48e-06)
Total affected t-2	-1.45e-05***	-9.31e-06***	-9.25e-06***	-9.40e-06***	-9.16e-06***	-8.19e-06***
	(1.27e-06)	(1.52e-06)	(1.49e-06)	(1.53e-06)	(1.57e-06)	(1.55e-06)
Total affected t-3	-1.12e-05***	-7.80e-06***	-7.73e-06***	-7.86e-06***	-7.68e-06***	-6.56e-06***
	(6.36e-07)	(5.57e-07)	(5.36e-07)	(6.36e-07)	(6.48e-07)	(8.07e-07)
Total affected t-4	-1.32e-05***	-8.80e-06***	-8.73e-06***	-8.87e-06***	-8.55e-06***	-7.47e-06***
	(7.29e-07)	(9.34e-07)	(9.42e-07)	(9.39e-07)	(9.70e-07)	(1.06e-06)
Total affected t-5	-1.01e-05***	-5.85e-06***	-5.81e-06***	-5.90e-06***	-5.67e-06***	-5.03e-06***
	(6.03e-07)	(1.02e-06)	(1.01e-06)	(1.09e-06)	(1.12e-06)	(1.05e-06)
Total affected t-6	-5.52e-06***	-2.54e-06***	-2.50e-06***	-2.51e-06***	-2.15e-06***	-1.62e-06***
	(1.09e-06)	(4.47e-07)	(4.55e-07)	(4.44e-07)	(4.43e-07)	(4.89e-07)
Total affected t-7	-7.75e-06***	-4.02e-06***	-4.01e-06***	-4.05e-06***	-3.76e-06***	-3.18e-06***
	(5.70e-07)	(1.17e-06)	(1.15e-06)	(1.17e-06)	(1.17e-06)	(1.09e-06)
Cumulative effect	-0.0000814***	-0.0000504***	-0.0000499***	-0.0000506***	-0.0000483***	-0.000041***
	(3.81e-06)	(6.54e-06)	(6.40e-06)	(6.62e-06)	(6.99e-06)	(7.60e-06)
Log GDP/capita		2.845***	2.772***	2.756***	2.679***	1.362*
		(0.211)	(0.264)	(0.270)	(0.364)	(0.763)
Population density			0.00864	0.00858	0.0112	0.00402
			(0.00782)	(0.00770)	(0.00878)	(0.00817)
Institutional index				-0.0361	-0.0282	-0.0360
				(0.0594)	(0.0554)	(0.0429)
Log R&D exp. t-1					0.241	-0.283
					(0.380)	(0.310)
Log total patents						0.554***
						(0.212)
Observations	832	832	832	797	705	704
No. of countries	52	52	52	50	50	50

*Note: Total affected is in thousands. All models include country and year fixed effects. Standard errors are clustered at the country level, presented in parenthesis; * p < 0.1, ** p < 0.05, *** p < 0.01*

Table C5: Patent counts in response to total damages.

VARIABLES	(1) Patent	(2) Patent	(3) Patent	(4) Patent	(5) Patent	(6) Patent
Total damage t	4.30e-05***	1.02e-05	1.04e-05	1.22e-05	1.27e-05	7.38e-06
	(1.29e-05)	(9.04e-06)	(9.11e-06)	(8.64e-06)	(9.29e-06)	(9.52e-06)
Total damage t-1	4.18e-05***	-1.82e-07	-1.19e-07	3.50e-06	6.52e-06	-1.14e-06
	(1.21e-05)	(8.99e-06)	(9.11e-06)	(9.24e-06)	(1.01e-05)	(9.87e-06)
Total damage t-2	7.45e-05***	2.77e-05***	2.77e-05***	3.09e-05***	2.95e-05***	1.72e-05*
	(9.06e-06)	(9.78e-06)	(9.81e-06)	(8.93e-06)	(9.74e-06)	(9.79e-06)
Total damage t-3	5.93e-05***	2.59e-05*	2.57e-05**	2.53e-05*	2.35e-05*	1.48e-05
	(1.34e-05)	(1.32e-05)	(1.30e-05)	(1.31e-05)	(1.39e-05)	(1.40e-05)
Total damage t-4	6.09e-05***	2.92e-05**	2.90e-05**	2.65e-05*	2.36e-05*	1.65e-05
	(1.13e-05)	(1.31e-05)	(1.30e-05)	(1.41e-05)	(1.41e-05)	(1.39e-05)
Total damage t-5	6.24e-05***	4.65e-05***	4.64e-05***	4.49e-05***	4.51e-05***	3.66e-05***
	(6.74e-06)	(9.61e-06)	(9.86e-06)	(1.03e-05)	(1.06e-05)	(1.20e-05)
Total damage t-6	6.42e-05***	6.20e-05***	6.18e-05***	5.92e-05***	5.71e-05***	5.07e-05***
	(9.38e-06)	(6.11e-06)	(5.87e-06)	(6.49e-06)	(6.89e-06)	(7.30e-06)
Total damage t-7	3.07e-05**	4.14e-05***	4.12e-05***	3.92e-05**	3.58e-05**	3.54e-05**
	(1.42e-05)	(1.51e-05)	(1.54e-05)	(1.57e-05)	(1.63e-05)	(1.64e-05)
Cumulative effect	0.000437***	0.0002426***	0.0002421***	0.0002417***	0.0002337***	0.0001775***
	(0.0000267)	(0.0000424)	(0.0000424)	(0.0000421)	(0.0000424)	(0.0000481)
Log GDP/capita		3.571***	3.557***	3.457***	3.565***	2.344***
		(0.542)	(0.552)	(0.490)	(0.488)	(0.634)
Population density			0.00155	0.00278	0.00698	0.00116
			(0.00666)	(0.00610)	(0.00749)	(0.00808)
Institutional index				0.0807*	0.110**	0.0729*
				(0.0481)	(0.0491)	(0.0413)
Log R&D exp. t-1					-0.121	-0.469
					(0.328)	(0.351)
Log total patents						0.548***
						(0.208)
Observations	832	832	832	797	705	704
Number of c_id	52	52	52	50	50	50

*Note: Total economic damages are in USD millions 2017 constant prices. All models include country and year fixed effects. Standard errors are clustered at the country level, presented in parenthesis; * p < 0.1, ** p < 0.05, *** p < 0.01*

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