Innovation as Adaptation to Natural Disasters

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Abstract

Can innovation be motivated by past natural disasters? Despite some recent research, the determinants of disaster-mitigating innovation are not well understood. Starting from a conceptual model combining perceived risk theory with the profit motive, this paper investigates the salience of innovation induced by natural disasters, using a unique dataset that includes U.S. patent data, and flood, drought, and earthquake damage data for the years 1977 to 2005. To address the potential endogeneity of disaster damage, I employ the control function approach with instrumental variables constructed from disaster intensity measurements. The results show that impact-reducing innovations at the state level respond to national disaster damage in the U.S. In general, the impact of natural disasters is not localized to a state–that is, disaster damage in a state also stimulates innovations in more-distant states.The findings in this paper highlight a policy role for the federal government in channelling and more effectively spurring impact-reducing innovations nationwide.

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☆**This is my job market paper. Comments are welcome. For the most up-to-date version, please check** `http://personal.uwaterloo.ca/h254li/`**.**

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1. Introduction

Natural disasters have a broad range of impacts and cause significant damage every year. From 1960 to 2014, natural disasters resulted in $15.6 billion in losses, injured 4,354 people, and killed 582 people per year in the U.S. Moreover, climate scientists suggest that climate change is likely to increase the hazard probability of natural disasters, such as floods, droughts, heat waves and cold spells, both in their frequency and intensity (Hallegatte, 2014; IPCC, 2012; Peterson et al., 2013). How do people reduce the impacts of natural disasters? Many studies argue that natural disasters are mostly a problem of under-development: less-developed areas may lack preventative measures and adequate infrastructure, and may thus be more vulnerable to natural disasters. In general, disaster damages do decrease with economic development and wealth, which seem to be part of a solution to protecting human lives and property from the increasing threat of natural disasters (Kahn, 2005; Toya and Skidmore, 2007; Mendelsohn et al., 2012).

However, several recent disasters, like Hurricane Sandy in 2012 in New York City and the Houston Flooding in 2016, both of which caused extensive losses even in affluent areas, reveal that economic development is not a panacea for natural disaster response. As shown by Hallegatte (2012), higher income does not always translate into better protection from and less exposure to natural hazards, and adaptive measures that account explicitly for reducing disaster risks need to be adopted to complement general economic development. Adaptive measures, including adoption of existing mitigating technologies and innovation of new technologies, can help reduce the impact of natural disasters and build resilience for future events. For example, the California droughts in recent years have spurred many innovations aimed at reducing the impact of droughts, such as new technologies related to sea water desalination and water-recycling systems. Although there appears to be a link between past disaster damage and the emergence of mitigating technologies, to date innovation as an adaptive response to natural disasters is not well understood.

This paper empirically examines the response of impact-reducing technological innovations to natural disasters, based on a conceptual model combining perceived risk theory and profit motivation. Natural disaster damage increases perceived risks and raises demand for impact-reducing technology, to which inventors may respond by increasing their relevant innovation output. Using a unique state-level dataset constructed from U.S. patent data and natural disaster data for the years 1977-2005, I explore the following questions: is impact-reducing innovation affected by the shock of past natural disasters and what is the magnitude of this response? Additionally, what is the scope of this response; is it nationwide or localized? Lastly, since innovation creates positive externalities, could policies be developed in order to stimulate impact-reducing innovations more effectively?

In the U.S., response to natural disasters is primarily the responsibility of local governments and the private sector, with a minor role for the federal government.[1] The Federal Emergency Management Agency (FEMA) is in charge of assessing a state's disaster declaration ex-post and for disbursing money to the state government for recovery assistance. Impact-reducing innovation as an adaptive measure is mostly conducted by the private sector, and there is no program at the federal level targeted specifically at impact-reducing innovations. As many papers in the literature suggest, innovation generates many substantial positive externalities, and hence reliance on the private sector will result in under-investment in innovation (Martin and Scott, 2000). This study offers some insights into the determinants of impact-reducing innovation as adaptation to natural disasters, and the findings have direct implications for policy.

The existing body of research on the impact of extreme weather and natural disasters focuses mainly on short-run and long-run economic growth.[2] There has been an increasing recognition of the fact that weather shocks and technological progress form an important channel of the climate-economy interface. Surprisingly, this link has been the subject of few studies. Crespo Cuaresma et al. (2008) examine how catastrophic risks affect technology transfer and capital updating, and find that the degree of catastrophic risk is negatively related to knowledge spillovers between industrialized and developing countries. Rodima-Taylor et al. (2012) and Chhetri and Easterling (2010) conduct case studies showing that weather realizations can stimulate impact-reducing innovation in agriculture. Taking a cross-country view, a study by Miao and Popp (2014) is the first attempt to examine risk-mitigating innovations induced by natural disasters. For domestic patent applications, they find positive responses to a country's past natural disaster damage, and no response to other countries' disaster damage for droughts and earthquakes. Hence, risk-

[1] More details about the disaster management system in the U.S. can be found in Mener (2007) and Kousky et al. (2016).

[2] For a survey of the climate-economy literature, see Dell et al. (2014).

mitigating innovation responds only to local disaster events, which seems to confirm the old saying that "necessity is the mother of invention." However, their results are likely to be determined by heterogeneity across countries (with respect to patent systems and overall innovation capacity), making it difficult to identify the mechanism and driving force of innovation aimed at reducing disaster impact. For instance, foreign innovators are less likely to respond to disasters in a country with poor patent protection (especially of foreign innovations) as their innovation may be appropriated easily, and hence this poor protection reduces the potential profitability of the research enterprise. In contrast, this study analyzes the response of innovation to national disasters at a subnational level, where crucial confounding factors affecting innovation (e.g., institutional quality and income) are significantly more homogeneous across sections. One would expect this approach to reveal a more accurate assessment of the interaction between disaster damages and the location of innovations.

In this paper, I propose a framework in which disaster damage increases perceived risks and self-protection needs of local communities, and profit motivates potential innovators in both *nearby and more-distant* regions to develop impact-reducing technologies. Using specific U.S. patent data and natural disaster damage data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS) for the period of 1977-2005, this subnational empirical study on floods, droughts, and earthquakes reveals that impact-reducing innovations do occur in response to damages caused by natural disasters, with some variation in scope across disaster type. For floods and droughts, disaster damage in a state spurs impact-reducing innovations in other states; that is, the response seems to be national in scope. Nevertheless, the response of disaster impact-reducing innovations to past earthquakes tends to be more localized: earthquake damage stimulates a significant amount of impact-reducing innovations in local and nearby states. In summary, impact-reducing innovations at the state level respond to national disaster damage in the U.S., and it is likely that profitability is the direct drive force of such innovations, especially for floods and droughts.

The results of this study provide important implications for how to respond to natural disasters. Due to the existing positive external effects, an exclusive reliance on markets to provide the correct incentives for disaster-related innovation is not likely to be efficient, how to effectively spur impact-reducing innovations is an important question for the public sector. Innovation as adaptation to natural disasters should be encouraged as part of a federal-level policy responding to natural disasters. According to the findings of this study, support for impact-reducing technology should be channeled to both *disaster-prone and more-distant* institutions and innovators, based on expected successful research potential. In the case of earthquakes, a case can be made for more directly supporting potential innovators in areas that are at elevated risk of such natural disasters.

Concerns about feedback effects of past innovations and disaster damage, as well as the possible endogeneity of disaster damage due to unobserved factors that affect impact-reducing innovations, are addressed using the control function approach. According to the climate-economy literature, natural disaster damage is mostly determined by the physical intensity of disasters. Hence, instrumental variables measuring disaster intensity are constructed from meteorological and geophysical data for floods, droughts, and earthquakes, respectively. I find robust evidence that innovation responds to disaster damages regardless of distance for floods and droughts, whereas the response is more localized for earthquakes. This study contributes to the empirical climate-economy literature by leveraging econometric methods that have been used in recent research in health economics and the economics of innovation.

This paper is structured as follows. Section 2 introduces the mechanism through which natural disasters spur innovation at a local and a national level. Section 3 presents the empirical model, followed by data description in Section 4. Section 5 discusses potential endogeneity of disaster damage, and reports estimation results. Innovation in response to regional disaster damage as a robustness check is explored in Section 6. Section 7 concludes the paper and discusses the policy implications of the main findings.

2. Natural Disasters and Innovation: a Framework for Analysis

This section provides a theoretical mechanism of how disaster damage impacts innovation. The elemental part of this mechanism is built on the theory of protection motivation from psychology. Individuals' risk perception (perceived severity and probability of events) has positive effects on self-protective behavior (Rogers, 1983; Maddux and Rogers, 1983). This theory of protection motivation has been applied to understand preparedness for climate change and natural disasters. O'Connor et al. (1999) examine the relationship between risk perceptions and willingness to address climate change and show that risk perceptions lead to changes in one's behavioral intentions. Looking more specifically at natural disasters, a number of studies find that an individual's risk perception of natural disasters can affect risk reduction behaviors and preparedness (Martin et al., 2009; Miceli et al., 2008; Mulilis and Lippa, 1990). Furthermore, prior experiences of disaster events increase risk perception of the future disaster and have positive impact on self-protection decisions (Cameron and Shah, 2015; Mishra and Suar, 2007; Greening and Dollinger, 1992; Weinstein, 1989). In summary, experiences and awareness of past natural disasters raise the perceived risks, which stimulate self-protection behavior.

Miao and Popp (2014) applied the above theory to a mechanism of innovation responding to natural disasters: a disaster shock increases the perceived risks and raises the demand for adaptive technologies, which motivates the private sector to invent newer and more cost-effective technologies for reducing future impacts of natural disasters. However, their framework and results do not recognize a crucial link in this process: why and how the private sector responds to the rising demand for adaptive innovation. Understanding this link is essential to reveal the geographical scope of impact-reducing innovation and to design potential public policy.

Essentially, profitability is the link between the rising demand and the response of innovation. The rising demand for impact-reducing technologies provides profit incentives, which motivate the private sector to develop more effective products and technologies that reduce impacts of future disasters. Hence, a natural disaster event in a single location provides profit incentives to the private sector, and potential innovators in different locations, regardless of the distance, may respond and innovate. One would expect such innovative responses to take place in the intranational market of the U.S., where production factors are highly mobile, and barriers among regional markets are generally low. Innovation of new technologies can be done in other locations, and products with new technologies can be traded to and adopted by disaster-prone areas. In addition, information required in the research and development (R&D) process (e.g. natural disaster events and previous patents) is often publicly available. As a result, disasters happening in one place may spur innovations anywhere in the country, and hence, innovation as a response to natural disaster is not localized to where disasters occur. In other words, innovations in a location should respond to natural disasters nationwide. This leads us to formulate the following:

Hypothesis 1: Disaster impact-reducing innovation in a state responds to nationally aggregated disaster damages.

Nonetheless, if a disaster type is highly concentrated in certain states, the national aggregated disaster is primarily determined by the disaster damage in those states. For example, earthquake events mostly happen in the west coast of the U.S., and the earthquake damage from those states, such as California and Oregon, makes up a large portion of the earthquake damage in the U.S. In this case, Hypothesis 1 would not be rejected even if the impact-reducing innovation is localized to those high-risk states. Therefore, in order to further unveil the geographical scope of impact-reducing innovations, national disaster damage is divided into disaster damage in a given state, and in the rest of the U.S. If disasters happening in one place stimulate innovations anywhere in the country, impact-reducing innovation in a state should respond to disaster damage from the rest of the country. This is stated in Hypothesis 2, which will be examined in Section 6:

Hypothesis 2: Disaster impact-reducing innovation in a state responds to disaster damages in other states.

Note that some disaster events strike two or more states. Moreover, geographic proximity leads neighboring states to share similar environmental characteristics. Therefore, it is possible that the response of impact-reducing patents is localized at a larger regional level. An extension of Hypothesis 2 at a regional level that groups a state and its neighboring states is examined in Appendix E.

3. Empirical Analysis

From the framework linking natural disasters and innovation, prior disasters affect one's risk perception, which increases the demand for adaptive technology pertaining to natural disasters. While the perceived risk itself is unobserved, it is closely determined by past disaster shocks $D_{jit-1}, ..., D_{jit-n}$, the current adaptive capacity C_{it}, and the local environmental profiles. Thus one can write,

$$R_{jit} = f\left(D_{jit-1}, ..., D_{jit-n}, C_{it}, \eta_i\right), \tag{1}$$

where η_i is the state fixed effects that account for the environmental profile and natural hazards in state i.

The adaptive capacity, which represents the preparedness to respond to natural disasters, is unobserved. A line of empirical research explores characteristics that affect the capacity to cope with natural disasters in human systems. Income level is widely confirmed to have an influence on a region's capacity to adapt to natural disasters (Kahn, 2005; Toya and Skidmore, 2007; Mendelsohn et al., 2012).[3] Second, innovation capacity is an important factor in measuring the adaptive capacity (DARA International, 2012). Moreover, disaster impact-reducing innovations in a state is directly influenced by the state's innovation capacity. Thus, the overall innovation capacity is a crucial variable and is captured carefully from both the output and the input of the innovation process. The output of innovation in a state is measured by its total patent counts. The input side is measured by the higher education research and development (R&D) expenditure and R&D tax credit rate, which is shown to provide financial incentives to invest in R&D (Bloom et al., 2002; Wilson, 2009).

Disaster impact reducing innovation responds to the growing demand of such innovation raised by past disaster damages. Therefore, innovation aimed at reducing the impact of disaster type j in state i in year t, V_{jit}, is constructed as a function of past disaster damages $D_{jit-1}, ..., D_{jit-n}$, and controlling for other possible determinants in $X_{it,t-1}$,

$$V_{jit} = f\left(D_{jit-1}, ..., D_{jit-n}, X_{it,t-1}, \eta_i\right). \tag{2}$$

Notice that disaster damage in year t is omitted since disaster events in the same year may happen *after* a patent application is filed in year t, and this introduces significant noise in the contemporaneous disaster damage. Lags of disaster damages are included for two reasons: first, perceived risks of natural disasters are affected by the current and past experiences. Second, the innovation process may take years before a patent application is filed. A patent application filed in year t may be the outcome of an R&D investment prompted by disasters that occurred several years before. $X_{it,t-1}$ includes four variables: the state-level per capita GDP in year t, total patent counts in state i in year t, the higher education R&D expenditure in year $t-1$ and the R&D tax credit rate in year $t-1$. Total patent counts in a state i in year t represent the overall innovation capacity and also control for potential changes in the patent system in year t

[3] Other factors such as institution quality, corruption and governance may also influence adaptive capacity in a country (Anbarci et al., 2005; Toya and Skidmore, 2007). However, heterogeneity of institution quality and governance within a country is much lower than that cross countries, which is one of the reasons for the state-level analysis in this paper.

as a change in the patent system should affect patent counts in general. Innovation is a gradual process and may take months to years of research. As a result, one-year lagged higher education R&D expenditure and R&D tax credit rate are used in the empirical analysis, and the regression results are robust to different time lags.

As the dependent variable is a non-negative count measure with no upper bound, count data models which rely on the exponential mean function are adopted for estimation. The basic model given in Eq. (2) can be modified to test the two hypotheses formulated in Section 2. The estimating equation employed to test Hypothesis 1 is,

$$E\left[V_{jit}|D,X\right] = exp\left(\sum_{k=1}^{m}\beta_k D_{jt-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{3}$$

where D_{jt-k} represents damages of disaster type j in year t aggregated at the national level, and η_i are state fixed effects. This model tests whether impact-reducing innovations on disaster type j in state i should respond to aggregate damages of disaster type j in the country.

As discussed in Section 2, in order to further unveil the geographical scope of impact-reducing innovation, Hypothesis 2 is tested using the following equation. Impact-reducing innovations of disaster type j in state i in year t are modeled as a function of the damage from disaster type j in the rest of the U.S. ($D_{j,-it-1}, ..., D_{j,-it-k}$), controlling for state i's past damage from disaster type j ($D_{jit-1}, ..., D_{jit-k}$) and other variables $\boldsymbol{X_{it,t-1}}$:

$$E\left[V_{jit}|D,X\right] = exp\left(\sum_{k=1}^{m}\beta_k D_{jit-k} + \sum_{k=1}^{m}\gamma_k D_{j,-it-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right). \tag{4}$$

4. Data

4.1. Patent Data

The dependent variable in our analysis is the total count of patents aiming at reducing impacts of a type of disasters (i.e. floods, droughts, or earthquakes). This data was constructed through an extensive identifying and matching process from the United States Patent and Trademark Office (USPTO) Patent Grant Bibliographic Text, which contains detailed patent information, such as titles, abstracts, patent classes, and inventors' addresses, of all granted patents since 1976.

First, patents aiming at reducing the impact of a particular type of disasters are identified for floods, droughts and earthquakes, respectively. In the patent literature, search criteria including both keywords and classes are the most common method to filter targeted patents. Miao and Popp (2014) use keywords and/or classes and subclasses to identify patents related to a type of disaster. However, their criteria are quite restrictive, which yield a very small subset of all patents aiming at reducing the impact of a certain type of disasters. Here I augmented their criteria by adding other related classes and subclasses containing disaster names and other keywords. For example, the search criteria for flood involves more than 20 keywords (e.g. "flood control" and "flood prevention") in seven classes (e.g. Class 405 "Hydraulic and earth engineering" and Class 52 "Static structures (e.g., buildings)"). According to such criteria, more expansive and yet accurate lists of patents for flood, droughts, and earthquakes are extracted. The search criteria generate 113 domestic patents pertaining to flood impact-reducing technologies, 69 patents for droughts, and 387 patents for earthquakes. A complete list of search criteria for floods, droughts and earthquakes related patents is given in Appendix A. To ensure robustness of results to the various search methods, different criteria are employed and the results can be found in A.12 in the Appendix.

With the identified patents, the next step is to match patents to states according to inventors' addresses. A main issue in this process is that co-inventorship exists in patents on disaster impact-reducing technology. Given that the dependent variable in this model measures innovative activities at the state level, all inventors should be considered instead of only the first inventor. Hence, one patent count is assigned to each inventor's residential state.[4] Nevertheless, for the case where a patent has multiple co-inventors from the same state, repeated counts of inventors to a state can potentially cause a biased measurement of innovative activities. To avoid this problem, only one patent count is assigned to the state if a patent has more than one inventor from the same state.[5] For example, if a patent has three inventors, two of whom reside in New York and one resides in Texas, one count is assigned to New York and one to Texas. Patent counts pertaining to floods, droughts, and earthquakes at the state level are given in Table A.13,

[4] Having co-inventors from different states is rare (e.g. about 2% in flood impact-reducing patents) in the samples from all search criteria. Thus, inflation of patent counts across state is unlikely to happen here.

[5] Another way is to assign $1/n$ to each inventor's residence state, as done in Hovhannisyan and Keller (2015). The empirical results are very close despite of different counting approaches.

and maps of those patents at the state level are plotted in Figure B.2, B.4, and B.6.

The total count of patents pertaining to a type of disaster is computed according to the above rules for each state, and sorted by application years. Since the average patent processing time by USPTO is about 28-35 months, the number of granted patent drop dramatically in the final years of the sample period (many patents are still being processed and hence they are not published in the granted patent database). Taking a conservative approach, which is also a prevalent procedure in the literature, the analysis in this paper is limited to five years before the ending year 2010.[6] Thus, granted patent information is collected from USPTO for the years from 1977-2010, but the empirical analysis is limited to the years from 1977-2005.

Another way to measure innovation is to count patent applications (both granted and declined). Patent applications have been published in the USPTO Patent Application Full-Text and Image Database (AppFT) since March 2001. However, patent application data are not quality-controlled and have three additional drawbacks which make it a less accurate measure than granted patent data. First, there are several exceptions to the publication rule of patent applications, under which whether to publish an application is subject to the applicant's preference and status.[7] For example, inventors of high-quality innovations tend to decline the publication of their patent applications to keep certain details confidential. Thus, published applications are only a subset of all patent applications, and this subset is not likely to be a random selection. From a cross matching of the granted patent data and patent application data, more than one third of the granted patents are not published in the patent application database in my final sample of patents pertaining to floods, droughts and earthquakes. Second, information carried in patent applications is less accurate than that of granted patents. Classes are self-identified by applicants in patent applications, whereas they are scrutinized and usually modified by patent examiners during the review process. As a result, patent applications filtered by search criteria, which are based on patent classes related to natural disasters, contain a large number of biased and irrelevant applications. Additionally, the location information of inventors may be missing or misreported in the patent application data, making it difficult to calculate patent counts at the state level.

[6] About 95% of granted patents were processed within five years in data sample.

[7] For further details, please check USPTO Manual of Patent Examining Procedure (MPEP) 1120.

4.2. Disaster Damage Data

Disaster data is retrieved from the Spatial Hazard Event and Losses Database for the US (SHELDUS^{TM}) developed by the Hazards & Vulnerability and Research Institute at the University of South Carolina. SHELDUS^{TM} contains economic losses (property damages and crop damages), fatalities and injuries for 18 types of natural hazard events.[8] The impact of disasters, which is the key explanatory variable in the model, is measured as economic losses from disaster events. A map of economic losses at the state level is plotted for each type of disaster, as shown in Figure B.1, B.3, and B.5. Generally speaking, economic losses are more representative than fatalities and injuries in measuring damage from natural disasters. Many disaster events, especially for droughts and floods, cause few fatalities in developed countries like the U.S. As for injuries, the number of total injuries cannot paint the full picture of disaster damage since the severity of injuries is difficult to rate and is usually not reported. In addition, economic losses from natural disasters represent the potential value of the impact-reducing technology market, which provides profit incentives for potential innovators.

Nevertheless, models with fatalities as main explanatory variables are also examined to explore the response of innovation to different measure of disaster impacts. The results are reported in Appendix D.

4.3. Instrumental Variables

The goal of this study is to identify the impact of natural disasters on innovations, however they both may be affected by unobserved time-varying elements, such as institution quality and overall technology level. For instance, efficiency of the local institution is associated with lower disaster damage and a higher level of innovation. In this case, the estimated effect on impact-reducing innovation pertaining to a type of disaster is negatively biased. To correct for this endogeneity, variables that contribute to explain disaster intensity are employed as instrumental variables (IVs), and the control function approach is applied in Section 5.2. Note that the impact of disaster damage is examined at both the national and the state level. Thus, disaster damage is aggregated at the national level and the state level, and two sets of IVs are calculated respectively.

[8] The 18 types are drought, earthquake, flooding, fog, hail, heat, hurricane/tropical storm, landslide, lightning, severe storm/thunder storm, tornado, tsunami/seiche, volcano, wildfire, wind, winter weather, avalanche, and coastal. This provides potential to extend this preliminary study to other disasters.

Instrumental variables used for flood, drought, and earthquake damage are summarized in Table 1.

Table 1: Summary of instrumental variables

Disaster type	Damage in an area	Instrumental variables
Floods	National	maxUSPalmerZ, USPalmerZ2.5
	State-level	maxPalmerZ, PalmerZ2.5
Droughts	National	minUSPDSI, USPDSI-3
	State-level	minPDSI, PDSI-3
Earthquakes	National	maxUSmag, USmag4.5
	State-level	maxmag, mag4.5

As suggested by the climate-economy literature, the impact of natural disasters is mostly determined by the intensity of disasters. Hence, a number of variables measuring the physical intensity of floods, droughts and earthquakes are used as IVs for disaster damage. The IVs for flood and drought damages are constructed from the Palmer indices retrieved from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).[9] The Palmer indices (e.g. the Palmer Z-index and the Palmer Drought Severity Index) are widely used in climatology and climate-economy studies to measure drought or wetness conditions across the U.S.

The Palmer Z-index measures monthly moisture conditions and abnormality in an area. Two instruments for flood damage are created based on the Palmer Z-index: the maximum Palmer Z-index in the given year in an area (i.e. a state or the U.S.), and the number of months with Palmer Z-Index greater than 2.5 in a given area.[10] Since flood damage is aggregated at the national level and the state level in Eq. (3) and (4), two sets of these IVs are calculated from national and state-level Palmer Indices respectively

IVs for drought damage are constructed from the Palmer Drought Severity Index (PDSI), which is calculated from precipitation, temperature, and soil moisture data and has been widely used to recognize abnormality of drought conditions in a region.[11] In a similar fashion to IVs

[9] NOAA is recently reformed as National Centers for Environmental Information (NCEI). The Palmer Indices are available at a division, state, regional and national levels. For further information about the Palmer Indices, please check `http://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp`

[10] A value more than 2.5 indicates above severe wetness condition.

[11] There are other Palmer indices that also measure drought conditions. One advantage of using the PDSI is that it provides insulation from the dependent variable, i.e. innovations pertaining to droughts. The PDSI is more

for flood damage, the minimum value of the PDSI in the given year and area (i.e. a state or the U.S.) and the number of months with PDSI smaller than -3 are generated as IVs for drought damage in a given area.[12]

Last, information on the magnitude of earthquakes is gathered from the Advanced National Seismic System (ANSS) Comprehensive Earthquake Catalog (ComCat) sponsored by the United States Geological Survey (USGS). Note that this catalog is event-based rather than location-based. Nevertheless, it also provides information on the nearest populated places.[13] This information of nearby communities is retrieved to locate each earthquake to one or more states. The maximum magnitude in the given year and the number of earthquakes with magnitudes greater than 4.5 are calculated at the national and the state level as IVs for national and state-level earthquake damage, respectively.

4.4. Other Controls

Disaster impact-reducing innovation is likely to correlate with the state's overall innovation activities. Three variables are used to measure the overall innovation activities in a state: total patent counts, R&D expenditures for Science and Engineering in higher education, and R&D tax credits as financial incentives to research investment. Total patents in a state are extracted from the same source (USPTO Patent Grant Bibliographic Text) and are assigned to each state using the same algorithm as the patents pertaining to impact-reducing technology. Higher education R&D expenditures for Science and Engineering from all sources (e.g. federal, state government, and private sources) are publicly available from the Higher Education Research and Development Survey (HERD) conducted by the National Science Foundation (NSF). Wilson (2009) calculates the effective state R&D tax credit rate for each state since 1982, when state R&D tax credits were implemented for the first time in history. Another control variable is state-level per capita GDP, which comes from the Bureau of Economic Analysis (BEA) for 1977-2013. The state-level GDP accounting method was changed in 1997, and there is a notable upward shift of GDP after 1997. Thus, a dummy variable indicating years post 1997 is added together with per capita GDP

exogenous and is expect to affect the dependent variable only through drought damage since man-made changes (e.g. increased irrigation and new reservoirs) that contain new technologies are not considered in its calculation

[12] A value of PDSI less than -3.0 indicates above severe drought conditions.

[13] For details, check documentation of the ANSS `http://earthquake.usgs.gov/data/comcat/data-eventterms.php#place`

in regression analysis.

Table 2 reports the summary statistics of main variables in the empirical analysis. After merging the various data sets, our sample has 1,479 observations of 50 states and the Washington D.C. in the U.S. A summary for patent counts and disaster damage by state can be found in A.13.

Table 2: Descriptive Statistics

Variables	Mean	Max	Min	Variance
Floods				
Patents	0.0764	5	0	0.1166
Total damage	0.0541	4.9469	0	0.0702
Droughts				
Patents	0.0467	3	0	0.0540
Total damage	0.0222	5.8092	0	0.0376
Earthquakes				
Patents	0.2542	17	0	1.4982
Total damage	0.0354	31.4382	0	0.7774
Other Variables				
Total patents	1.5205	30.933	0.015	7.4911
Per capita real GDP	27.2351	163.965	9.7039	263.0889
Effective state tax credit rate	-0.0117	0.2	-37.9457	0.9755
Higher edu R&D expenditure	0.5148	6.8104	0.0155	0.5054

Number of observations for all variables is 1,479 for 50 states and one district in the U.S. Total patents are in thousand counts. Total damage and higher edu R&D expenditure is in billion dollars, and per capita real GDP is in thousand dollars. All dollar terms are adjusted to 2013.

5. Empirical Discussion and Results

Since the dependent variable is the number of granted patents on impact-reducing technology (of floods, droughts, and earthquakes respectively), count data models are applied to estimate Eq. (3) and (4). A conditional Poisson distribution of the dependent variable has been the most common assumption in the count data literature, given the attractive properties of its maximum likelihood estimators (Cameron and Trivedi, 2013). The Poisson quasi-maximum likelihood estimator (Poisson QMLE) is also robust to distributional misspecification, i.e. when the outcome variable conditional on the explanatory variables does not have a Poisson distribution (e.g., equidispersion is not satisfied), provided the conditional mean is correctly specified. Moreover, the pooled Poisson QMLE does not require strict exogeneity of regressors ($E[u_t|D_s] = 0$, for $\forall s$)

for consistency (Cameron and Trivedi, 2013; Wooldridge, 2010). In the empirical models, Eq. (3) and (4), innovations at time t may reduce disaster damage in future years, implying that previous disaster damage is weakly exogenous to innovations ($E[u_t|D_s] = 0$, for $s \leq t$). In this case, the pool Poisson QMLE still provides consistent estimates. Therefore, to begin with, Eq. (3) and (4) are estimated by the pooled Poisson QMLE with robust standard errors clustered on state to account for serial correlation. Nevertheless, the Poisson distributional assumption of equidispersion is often rejected in the data. In the case of overdispersion, standard errors tend to be conservative and cause inflation of the t-stat in Poisson estimates. For comparison, negative binomial (NB) models are also estimated, and in general they provide similar results with the Poisson QMLE for floods and droughts.

However, a weakness of the pooled Poisson or NB model is that coefficient estimates are biased in the presence of heterogeneity across groups. In terms of natural disasters, there is a significant diversity of environmental profiles and disaster risks across states. For example, floods happen mostly in the south, while droughts are more concentrated in the western part of the U.S. Hence it is necessary to control for a state's intrinsic characteristics, which are crucial for disaster types and damage. The Poisson fixed effect (Poisson FE) with multiplicative fixed effects, which control for states' time-invariant characteristics, provides consistent estimates if strict exogeneity of regressors is assumed. Eq. (3) and (4) are estimated with the Poisson FE model with robust standard errors that fix serial correlation (Cameron and Trivedi, 2005). From the summary in Table 2, patents pertaining to floods and droughts have unconditional variances less than twice that of the unconditional means, and hence overdispersion is not likely to be a concern (Cameron and Trivedi, 2013). Although the variance of patents is much larger than the mean for earthquakes, the large variance is mostly attributed to heterogeneity across states, and overdispersion can be significantly reduced after controlling state fixed effects. In case that overdispersion still exhibits with the Poisson FE model, a conditional likelihood method for NB fixed effect (NB FE) proposed by Hausman et al. (1984) is applied for comparison.[14]

[14] Note that Allison and Waterman (2002) explains that the NB FE method proposed by Hausman et al. (1984) is not qualified as a true FE model due to the incidental parameters problem. However, the impact of this problem in practice is still unclear.

5.1. Results

The above four approaches are applied to Eq. (3) and (4) for floods, droughts and earthquakes. The response of innovation in a state to the national damage is reported in Tables 3, 4, and 5 for floods, droughts, and earthquakes, respectively. The individual coefficient of disaster damage lags is the short term (yearly) effect of an increase in disaster damage, while the cumulative effect, which is a linear combination of coefficients of all the disaster damage lags, estimates the long term change of innovation. Five-year distributed lags are selected for the reported models based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

Table 3: Patent counts in response to national flood damage

Floods	(1) Pooled Poisson	(2) Pooled NB	(3) Poisson FE	(4) NB FE
D_{t-1}	0.0965*	0.0665	0.0827*	0.0877*
	(0.0458)	(0.0385)	(0.0405)	(0.0349)
D_{t-2}	0.142***	0.123***	0.128***	0.134***
	(0.0286)	(0.0326)	(0.0268)	(0.0312)
D_{t-3}	0.0679*	0.0596	0.0522*	0.0570
	(0.0271)	(0.0329)	(0.0259)	(0.0392)
D_{t-4}	-0.000894	0.00118	-0.0168	-0.0104
	(0.0482)	(0.0439)	(0.0480)	(0.0474)
D_{t-5}	0.0622	0.0665*	0.0513	0.0532
	(0.0350)	(0.0326)	(0.0317)	(0.0353)
Cumulative Effect	0.367***	0.317***	0.297***	0.322**
	(0.0844)	(0.0989)	(0.0763)	(0.110)
GDP per capita	-0.00220	-0.000291	0.00308	-0.00161
	(0.0108)	(0.0104)	(0.0270)	(0.0265)
Total patents	0.0180	0.0251	0.0435	0.0345
	(0.0559)	(0.0772)	(0.0411)	(0.0569)
R&D tax credits	0.0310	0.0449	5.730	4.879
	(0.0341)	(0.0393)	(4.937)	(4.942)
Higher edu R&D exp	0.584	0.674	-0.0852	-0.00131
	(0.328)	(0.381)	(0.282)	(0.337)
post_1997	-0.0971	-0.144	0.0581	0.131
	(0.305)	(0.316)	(0.652)	(0.664)
N	1479	1479	899	899
States	51	51	31	31
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Across floods, droughts, and earthquakes, the long term impacts of natural disasters are generally significant and provocative on patents pertaining to a type of disaster. The short term effect, however, is less consistent across time due to the nature of disaster events and the

Table 4: Patent counts in response to national drought damage

Floods	(1) Pooled Poisson	(2) Pooled NB	(3) Poisson FE	(4) NB FE
D_{t-1}	0.299***	0.301***	0.285***	0.298***
	(0.0637)	(0.0643)	(0.0661)	(0.0783)
D_{t-2}	0.0942	0.0954	0.0791	0.0927
	(0.102)	(0.101)	(0.0960)	(0.109)
D_{t-3}	0.247***	0.250***	0.234***	0.245**
	(0.0674)	(0.0688)	(0.0678)	(0.0754)
D_{t-4}	0.219***	0.218***	0.189**	0.218**
	(0.0607)	(0.0613)	(0.0644)	(0.0769)
D_{t-5}	0.235**	0.236**	0.217**	0.234***
	(0.0718)	(0.0719)	(0.0747)	(0.0645)
Cumulative Effect	1.093***	1.099***	1.004***	1.089***
	(0.191)	(0.194)	(0.199)	(0.244)
GDP per capita	0.00292	0.00295	0.151**	0.00412
	(0.00901)	(0.00921)	(0.0585)	(0.0106)
Total patents	-0.0237	-0.0224	0.00643	-0.0163
	(0.0253)	(0.0265)	(0.0381)	(0.0554)
R&D tax credits	1.348	1.312	2.372	1.708
	(2.390)	(2.408)	(6.019)	(3.149)
Higher edu R&D exp	0.531***	0.538***	-0.225	0.512*
	(0.123)	(0.135)	(0.282)	(0.248)
post_1997	1.450**	1.446**	-1.892	1.401**
	(0.487)	(0.486)	(1.190)	(0.427)
N	1479	1479	928	928
States	51	51	32	32
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

innovation process. The occurrence of natural disasters is inconsistent across years, for example, a significant disaster event in one year and several small disaster events in another year). The impact of a significant disaster can be much larger than that of several small events. Moreover, the innovation process is also less predictable, and patents, as an outcome of this process, may not be generated every year. Thus, it is expected that the individual yearly effect is not all positive and significant. Nevertheless, the long-term cumulative effect presents a more accurate impact of natural disasters.[15]

Patents aimed at reducing the impact of floods respond positively to past national flood damage. One billion dollars of flood damage in the U.S. can lead to a 35% increase in impact-

[15] Another possibility is substantial collinearity as a result of the multiple lags in the model. The individual coefficient of disaster damage may not be properly estimated, but the linear combination of the entire bundle of collinear variables is well-estimated in general (Wooldridge, 2009).

Table 5: Patent counts in response to national earthquake damage

	(1) Pooled Poisson	(2) Pooled NB	(3) Poisson FE	(4) NB FE
D_{t-1}	0.0176**	0.00211	0.0327***	0.0316***
	(0.00599)	(0.0145)	(0.00703)	(0.00951)
D_{t-2}	0.0101	-0.0154	0.0260**	0.0229*
	(0.00718)	(0.0219)	(0.00931)	(0.0112)
D_{t-3}	0.0546*	-0.00168	0.0174	0.0113
	(0.0215)	(0.0154)	(0.0110)	(0.0106)
D_{t-4}	0.0592***	0.0188	0.0246***	0.0229**
	(0.0139)	(0.0116)	(0.00710)	(0.00868)
D_{t-5}	0.0478***	0.00942	0.0210**	0.0176
	(0.0137)	(0.0113)	(0.00648)	(0.00915)
Cumulative Effect	0.189***	0.0132	0.122***	0.106***
	(0.0501)	(0.0453)	(0.0272)	(0.0274)
GDP per capita	-0.0409	-0.0111	-0.0424	-0.0437
	(0.0475)	(0.0130)	(0.0435)	(0.0320)
Total patents	0.00578	0.156	-0.0682**	-0.0583*
	(0.0179)	(0.239)	(0.0227)	(0.0270)
R&D tax credits	0.0135	4.784	7.574*	6.307*
	(0.0897)	(6.835)	(3.292)	(2.460)
Higher edu R&D exp	1.132***	0.997	0.0364	0.0167
	(0.191)	(0.783)	(0.149)	(0.193)
post_1997	-0.817	-0.152	1.487	1.640*
	(0.572)	(0.421)	(1.125)	(0.832)
N	1479	1479	986	986
States	51	51	34	34
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

reducing patents in a state in the next five years on average, with small variations across methods used in (1)-(4) in Table 3. The Louisiana Flooding in August in 2016, which caused a $10 billion loss, would spur flood impact-reducing patents across states by 350% in the next five years.

Compared to floods, there is a longer stimulating effect on impact-reducing innovations pertaining to droughts. Across all of the models presented in Table 4, there is evidence of a significant and positive short-term and long-term effect of drought damage on patents pertaining to droughts. In 2015, drought conditions plagued western states (e.g., California, Nevada and Oregon) for more than six months and caused $4.6 billion in losses. The size of the cumulative effect suggests that, at the state level, patents aimed at reducing the impact of droughts would increase by 790% on average in the next five years.

The results for earthquakes vary from methods (1) to (4) in Table 5. Compared to pooled

Poisson and pooled NB, the results are very close for Poisson FE and NB FE: the cumulative effect and most yearly effects are positive and significant. This implies that a state's intrinsic characteristics (e.g. natural hazard profiles) are crucial in analyzing the impact of earthquake damages. Since earthquakes are geographically concentrated in several states where plates motion is active (e.g., California, Oregon, and South Carolina), the intrinsic characteristics of states, such as locations, should be controlled by state fixed effects. Thus, the estimates by pooled Poisson and pooled NB are less likely to be consistent.[16] The cumulative effects in (3) and (4) of Table 5 reveal that $1 billion losses from earthquakes in the U.S. would spur about 11-13% more patents on earthquake impact-reducing technology in a state in the next five years.

5.2. Endogeneous Disaster Damages

In previous regression analysis, disaster damages are assumed to be exogenous. However, if disaster impact-reducing innovations affect the disaster outcome in later years, disaster damage is only weakly exogenous ($E(u_{it}|D_{is}) = 0, s \leq t$). In that case, the Poisson FE model, which requires strict exogeneity ($E(u_{it}|D_{is}) = 0, \forall s$), cannot provide consistent estimates. Furthermore, weakly exogenous disaster damage may become endogenous if innovation and disaster damage respond simultaneously to some unobserved exogenous shocks. Miao and Popp (2014) suggest that in their cross-country study, both innovation activities and disaster damages in a country may be influenced by unobservable time-varying elements, such technology level and institution quality of that country.

However, since the focus of this paper is intentionally sub-national, endogeneity of disaster damage should be inspected according to the level of analysis. As stated in Hypothesis 1, innovation in a state may respond to aggregate disaster damage at the national level. In this case, unobserved factors affecting disaster damage in the wider U.S., such as federal institution quality and technology level, are not likely to account for disparities in innovation across states. Additionally, as explained in Section 1, the federal government performs a minor role in disaster response and does not have any program explicitly supporting innovation pertaining to natural disasters. Thus, endogeneity of national disaster damage in Eq. (3) seems to be substantially reduced. Nevertheless, for the suspected endogeneity of disaster damage, instrumental variables

[16] In addition, the dependent variable, patents pertaining to earthquakes, exhibits strong overdispersion without conditional on state fixed effects. Estimates by pooled Poisson is likely to vary from pooled NB.

(IVs) and the control function (CF) approach can be used to correct the potential endogeneity bias.

As noted by Wooldridge (2010) and Cameron and Trivedi (2005), one way to address endogeneity in panel count data is the control function (CF) approach (also called two-stage residual inclusion (2SRI)), which has been widely applied in recent literature such as health, crime, and innovation economics (Terza et al., 2008; Cameron and Trivedi, 2013; Hovhannisyan and Keller, 2015).[17] This method was initially suggested by Hausman et al. (1984), and consistent CF methods have been developed for many specific non-linear models (Rivers and Vuong, 1988; Wooldridge, 1997; Blundell and Powell, 2004).

The application of the CF approach is quite straightforward: endogeneous regressors are regressed on all exogenous variables in the first stage (regression on the control function); in the second stage, first-stage residuals (instead of first-stage predictors) are included as additional regressors. The CF approach has several advantages such as consistent estimates with nonlinear models and computational simplicity, though a stronger assumption of IVs is required.[18] As described in Section 4, variables that measure disaster intensity are employed as instrumental variables (IVs). The main identification assumption is that disaster intensity affect impact-reducing innovations only by being correlated with disaster damage. Also, disaster intensity cannot be correlated with other factors affecting patents pertaining to natural disasters.

The control function proposed for Eq. (3) is the residual of a regression of national disaster damage on the all exogenous variables:

$$D_{jt} = \boldsymbol{\theta_1} \boldsymbol{Z}_{jt} + \boldsymbol{\theta_2} \boldsymbol{X}_{it,t-1} + \eta_i + \omega_{jit}, \tag{5}$$

where Z_{jt} is the set of two IVs for national disaster damage of disaster type j, and ω_{jit} is the residual to be estimated. In the first stage, the reduced form Eq. (5) is estimated with an ordinary least squares regression to obtain the residual $\hat{\omega}_{jit}$. In the second stage, one-year lag of

[17] Several moment-based methods have been developed for count data to deal with weakly exogeneity and endogeneity. However, one major drawback of generalized method of moments (GMM) estimators is computational complexity, and availability of estimates is subject to variation in the data and model complexity (e.g., convergent problem with estimators), which is the case in this study. Nonetheless, GMM IV methods are discussed in Appendix F

[18] IVs need to be *statistically independent*, rather than mean independent as assumed in GMM IV estimation, of other factors that affect the dependent variable

Table 6: Patent counts in response to national disaster damage with the control function

	(1) Floods	(2) Droughts	(3) Earthquakes
D_{t-1}	0.0874*	0.262*	0.0902
	(0.0407)	(0.129)	(0.0553)
D_{t-2}	0.129***	0.0862	0.0274
	(0.0310)	(0.123)	(0.0209)
D_{t-3}	0.0594	0.246**	0.0195
	(0.0368)	(0.0781)	(0.0186)
D_{t-4}	-0.00416	0.185*	0.0265*
	(0.0587)	(0.0793)	(0.0129)
D_{t-5}	0.0458	0.219*	0.0260
	(0.0367)	(0.0917)	(0.0135)
Cumulative Effect	0.317**	0.998***	0.189*
	(0.106)	(0.258)	(0.0940)
GDP per capita	0.00154	0.148*	-0.0354
	(0.0492)	(0.0680)	(0.0718)
Total patents	0.0403	0.00530	-0.0656
	(0.152)	(0.232)	(0.203)
R&D tax credits	5.202	2.382	9.025
	(5.192)	(10.90)	(4.781)
Higher edu R&D exp	-0.0993	-0.212	-0.0954
	(0.703)	(0.882)	(0.561)
post_1997	0.0987	-1.805	1.458
	(1.048)	(1.460)	(1.767)
Control function	-0.0950	0.0384	-0.0605
	(0.0982)	(0.156)	(0.0522)
N	1392	1392	1479
States	48	48	51

Column 1 and 2 list results for 48 contiguous states since NCDC does not provide Palmer indices for Alaska, Hawaii and Washington D.C.; standard errors are presented in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the residual, $\hat{\omega}_{jit-1}$, is included in the Poisson MLE regression of Eq. (3) with state fixed effect.

Although Eq. (3) consists of multiple distributed lags of disaster damage, including multiple control functions (i.e. $\hat{\omega}_{jit-1}, ..., \hat{\omega}_{jit-n}$) is redundant and lead biased estimates of disaster damage. The intuition is that one control function can account for the unobserved variables that affect both innovation and disaster damage.[19] $\hat{\omega}_{jit-1}$ is selected since it contains most information of all past shocks, and is the best control for the endogeneity of disaster damage. Shocks that affect disaster damage usually are not transient. For instance, a reform of the national disaster response system would have long term effect on disaster damages; innovations, such as reinforced

[19] See Wooldridge (2007) for an example of multiple endogenous variables and one control function.

concrete structure, have lasting effects on reducing disaster damage once being constructed or installed. Moreover, including multiple lags of residual is not recommended in the second stage due to multicollinearity (with each other and with lags of disaster damage).

Table 6 presents estimates using the CF approach for national aggregated disaster damage.[20] Compared to those in Table 3, 4, and 5, where national disaster damage is treated as an exogenous variable, the long-term cumulative effects are positive and similar in magnitude. These results confirm the previous finding that, for all three types of disasters, impact-reducing innovation in a state is stimulated by nationally aggregate disaster damage. In addition, the endogeneity seems to be minimal in the context of national disaster damage, especially for floods and droughts. One billion dollars in losses would spur 37% and 171% more impact-reducing innovations pertaining to floods and droughts respectively, and the results are similar to those without IVs in Table 3 and 4. Nevertheless, for earthquakes, the cumulative effect of damage is larger than those in columns (3) and (4) of Table 5, which verifies the conjecture that endogeneity of disaster damage leads to a negative bias of the coefficient. Earthquake damage of $1 billion would result in a 21% increase in innovations pertaining to earthquakes, while the number is 11-13% without IVs. A possible reason is that both earthquake events and impact-reducing innovations are concentrated in the high-risk area, e.g., California. The national earthquake damage is highly correlated with the disaster damage in the high-risk states, and hence is less exogenous to impact-reducing innovation, of which a substantial portion also locates in the high-risk states.

6. Robustness Checks

As discussed in Section 2, if a disaster type is highly concentrated in certain states, such as earthquakes in the U.S., the national aggregate disaster is primarily determined by the disaster damage in those states. In this case, impact-reducing innovation in a state seems to respond to national disaster damage even if the impact-reducing innovation is actually localized to the high-risk states. Therefore, Eq. 4 is estimated to further investigate the geographical scope of impact-reducing innovation-more specifically, whether impact-reducing innovation as a response to natural disasters is indeed nationwide.

[20] The results of first stage regressions, given in Eq. (5), are reported in column 1 in Table C.14 and C.15.

Table 7: Patent counts in response to flood damage at the state level

	(1)	(2)	(3)	(4)
	Pooled Poisson	Pooled NB	Poisson FE	NB FE
D_{-it-1}	0.0710*	0.0549	0.0632*	0.0699
	(0.0358)	(0.0320)	(0.0295)	(0.0366)
D_{-it-2}	0.139***	0.125***	0.133***	0.140***
	(0.0302)	(0.0342)	(0.0269)	(0.0314)
D_{-it-3}	0.0500	0.0479	0.0460	0.0510
	(0.0307)	(0.0335)	(0.0279)	(0.0394)
D_{-it-4}	-0.00293	-0.000101	-0.0126	-0.00590
	(0.0464)	(0.0445)	(0.0465)	(0.0467)
D_{-it-5}	0.0585	0.0591	0.0542	0.0574
	(0.0338)	(0.0325)	(0.0317)	(0.0356)
Cumulative Effect	0.316***	0.287**	0.283***	0.312**
	(0.0811)	(0.0920)	(0.0775)	(0.108)
D_{it-1}	0.479**	0.444*	0.474	0.476
	(0.158)	(0.226)	(0.253)	(0.255)
D_{it-2}	0.137	0.109	-0.109	-0.0823
	(0.144)	(0.177)	(0.251)	(0.356)
D_{it-3}	0.457**	0.438*	0.333	0.381
	(0.155)	(0.216)	(0.212)	(0.254)
D_{it-4}	0.289	0.122	0.0629	0.0731
	(0.224)	(0.277)	(0.236)	(0.304)
D_{it-5}	0.229	0.335	0.0290	0.00687
	(0.276)	(0.236)	(0.302)	(0.274)
Cumulative Effect	1.591**	1.448*	0.791	0.855
	(0.616)	(0.664)	(0.588)	(0.705)
Real GDP per capita	0.000460	0.00151	0.00553	0.00269
	(0.00997)	(0.00998)	(0.00828)	(0.0118)
Total patents	-0.0163	0.00145	0.0288	0.0208
	(0.0597)	(0.0869)	(0.0516)	(0.0625)
R&D tax credits	0.0337	0.0461	5.137	4.296
	(0.0342)	(0.0382)	(5.016)	(4.973)
Higher edu R&D exp	0.693*	0.701	0.00463	0.105
	(0.320)	(0.371)	(0.244)	(0.352)
post_1997	-0.124	-0.139		
	(0.299)	(0.303)		
N	1479	1479	899	899
States	51	51	31	31
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Patent counts in response to drought damage at the state level

	(1) Pooled Poisson	(2) Pooled NB	(3) Poisson FE	(4) NB FE
D_{-it-1}	0.267***	0.268***	0.262***	0.262**
	(0.0681)	(0.0685)	(0.0720)	(0.0833)
D_{-it-2}	0.0729	0.0745	0.0771	0.0771
	(0.128)	(0.127)	(0.105)	(0.114)
D_{-it-3}	0.262***	0.264***	0.252***	0.252**
	(0.0680)	(0.0694)	(0.0683)	(0.0771)
D_{-it-4}	0.215**	0.215**	0.193**	0.193*
	(0.0678)	(0.0682)	(0.0682)	(0.0855)
D_{-it-5}	0.245**	0.246**	0.234**	0.234***
	(0.0748)	(0.0749)	(0.0776)	(0.0695)
Cumulative Effect	1.0625***	1.0669***	1.0711***	1.0184***
	(0.209)	(0.212)	(0.194)	(0.259)
D_{it-1}	0.826***	0.827***	0.522***	0.522*
	(0.0917)	(0.0942)	(0.0862)	(0.223)
D_{it-2}	0.478	0.488	0.140	0.140
	(0.319)	(0.316)	(0.203)	(0.507)
D_{it-3}	-1.055	-1.080	-1.710	-1.710
	(0.687)	(0.698)	(1.000)	(1.465)
D_{it-4}	0.465**	0.477**	0.291**	0.291
	(0.168)	(0.175)	(0.107)	(0.305)
D_{it-5}	-0.00775	-0.00243	-0.203	-0.203
	(0.434)	(0.428)	(0.262)	(0.713)
Cumulative Effect	0.707	0.710	-0.681	-0.960
	(1.056)	(1.059)	(0.821)	(1.947)
Real GDP per capita	0.00308	0.00311	0.158*	0.158*
	(0.00899)	(0.00912)	(0.0658)	(0.0619)
Total patents	-0.0227	-0.0217	0.00556	0.00556
	(0.0228)	(0.0236)	(0.0395)	(0.0729)
R&D tax credits	1.255	1.223	3.262	3.262
	(2.409)	(2.422)	(6.930)	(6.368)
Higher edu R&D exp	0.527***	0.532***	-0.310	-0.310
	(0.129)	(0.138)	(0.312)	(0.466)
post_1997	1.525**	1.522**	-1.963	-1.963
	(0.529)	(0.528)	(1.302)	(1.424)
N	1479	1479	928	928
States	51	51	32	32
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Patent counts in response to earthquake damage at the state level

	(1) Pooled Poisson	(2) Pooled NB	(3) Poisson FE	(4) NB FE
D_{-it-1}	-0.0120	0.00104	0.0204	0.0222
	(0.0173)	(0.0152)	(0.0136)	(0.0126)
D_{-it-2}	-0.0334	-0.0155	0.00260	0.00503
	(0.0283)	(0.0236)	(0.0252)	(0.0160)
D_{-it-3}	0.0115	-0.000630	0.00608	0.00421
	(0.0197)	(0.0159)	(0.0141)	(0.0126)
D_{-it-4}	0.0308	0.0214	0.0255*	0.0241*
	(0.0179)	(0.0118)	(0.0113)	(0.0100)
D_{-it-5}	0.0234	0.0114	0.0177	0.0170
	(0.0135)	(0.0115)	(0.00944)	(0.0106)
Cumulative Effect	0.0203	0.178	0.0723	0.0726*
	(0.0661)	(0.465)	(0.0406)	(0.0331)
D_{it-1}	0.0633***	-0.0198	0.0414***	0.0427***
	(0.0192)	(0.0236)	(0.00448)	(0.0120)
D_{it-2}	0.0593**	-0.0436	0.0392***	0.0410***
	(0.0191)	(0.0270)	(0.00455)	(0.0124)
D_{it-3}	0.0915***	-0.0767	0.0304***	0.0284*
	(0.00565)	(0.0450)	(0.00664)	(0.0141)
D_{it-4}	0.0822***	-0.105	0.0259***	0.0246
	(0.00506)	(0.0573)	(0.00605)	(0.0137)
D_{it-5}	0.0704***	-0.131*	0.0256***	0.0214
	(0.00622)	(0.0600)	(0.00370)	(0.0154)
Cumulative Effect	0.367***	-0.376	0.163***	0.158***
	(0.0437)	(0.192)	(0.0150)	(0.0422)
Real GDP per capita	-0.0198	-0.0140	0.0152	-0.0304
	(0.0284)	(0.0140)	(0.0116)	(0.0316)
Total patents	-0.0748*	0.228	-0.0652***	-0.0683*
	(0.0307)	(0.187)	(0.0174)	(0.0285)
R&D tax credits	0.0428	5.896	7.534*	6.389**
	(0.109)	(6.657)	(3.520)	(2.354)
Higher edu R&D exp	1.266***	0.888	-0.0916	0.0243
	(0.159)	(0.627)	(0.118)	(0.189)
post_1997	-0.660	-0.174	1.148	1.302
	(0.507)	(0.422)	(1.130)	(0.825)
N	1479	1479	986	986
States	51	51	34	34
Time period	1977-2005	1977-2005	1977-2005	1977-2005

Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The empirical strategy is the same with that in Section 5. The regression results of innovation on disaster damage at the state level are presented in Table 7, 8, and 9 for floods, droughts, and earthquakes. For floods, the cumulative effects of disaster damage from the rest of the U.S. are positive and significant, as shown in the first cumulative effective from column (1) to (4) of Table 7. This indicates that flood impact-reducing innovation in a state is positively affected by disaster damage from other states. Also, the estimates for droughts across different methods show similar consistency: the cumulative effects of disaster damage from other states are positive and significant. Therefore, for floods and drought, disaster damage does not necessarily spur patents in local areas. Rather, disaster damage can stimulate patents somewhere more distant in other states. Combining the results from model (3), where innovation is stimulated by the national disaster damage, the response of impact-reducing innovation seems to be national rather than localized to where floods and droughts occur.

The results for earthquakes vary from methods (1) to (4) in Table 9. As discussed in Section 5.1, states' intrinsic characteristics, such as location and earthquake hazard, are crucial in analyzing the impact of earthquake damages. Therefore, models with state fixed effects in (3) and (4) of Table 9 provide consistent estimates compared to pooled models in (1) and (2). Moreover, the variance of patents pertaining to earthquake impact-reducing technology is much larger than its mean. Although the large variance is mostly attributed to heterogeneity across states, overdispersion may still exhibit even if state fixed effects are controlled. In this case, NB FE is preferred to Poisson FE.

In contrast to the results for floods and droughts, there is mixed evidence that innovation is stimulated by earthquake damage in other states: the cumulative effects of earthquake damages in other states are positive but only significant with NB FE. However, impact-reducing patents pertaining to earthquakes respond positively to local earthquakes. Therefore, it seems that the response of innovations to earthquake damage comes from many states nationwide, but also substantially localized. A possible explanation is that the expected market of impact-reducing technology is smaller than that of floods or droughts. Earthquakes are highly geographically concentrated, and disastrous earthquake events are rare and less predictable compared to floods and droughts. Thus, the expected market size and market value of earthquake impact-reducing technology is relatively small and hence cannot provide sufficient profit incentives to potential innovators across states. In addition, first-hand information and experience in earthquakes may be an important input in the innovation process. Local innovators have the advantages of obtaining such information at a lower cost, which lead to prosperity of local innovations.

6.1. Endogenous Disaster Damage

The model in Eq. (4) examines whether impact-reducing innovation in a state responds to disaster damage in other states, controlling for the disaster damage in the given state. In this model, unobserved factors that affect innovation, such as efficiency and transparency of the local government, may also impact the disaster outcome in this region given that local governments share a major role in natural disaster management. In this case, disaster damage in a state may be endogenous, but the estimated effect on impact-reducing innovation is negatively biased, which is favourable to our findings.[21] Nevertheless, for the suspected endogeneity of disaster damage in Eq. (4), instrumental variables (IVs) and the control function (CF) approach can be used to correct the potential endogeneity bias.

In Eq. (4), disaster damage is disaggregated to a state level and the rest of the U.S. The results in Section 5.2 suggest endogeneity between national disaster damage and innovation in a state is less of a concern. Thus, it is plausible that disaster damage from the rest of the U.S. tends to be exogenous to impact-reducing innovation in a given state. Still, state-level disaster damage appears to be endogenous to unobserved factors that also affect innovation in a state. Therefore, disaster damage from state i, D_{jit}, is assumed to be endogenous, and the control function for Eq. (4) is the residual from

$$D_{jit} = \boldsymbol{\theta_1} \boldsymbol{Z}_{jit} + \boldsymbol{\theta_2} \boldsymbol{X}_{it,t-1} + \eta_i + \omega_{jit}, \tag{6}$$

where Z_{jit} is the set of two IVs for state-level damage of disaster type j, and ω_{jit} is the residual to be estimated. To obtain the residual $\hat{\omega}_{jit}$, Eq. (6) is estimated using the ordinary least squares regression with state fixed effects in the first stage.[22] In the second stage, a one-year lag of the residual, $\hat{\omega}_{jit-1}$, is included in the Poisson regression of model (4) with state fixed effect.

The estimated effects with the CF approach are presented in Table 10. The first cumulative

[21] Within a country, progress in adaptation technology (e.g., air conditioning and irrigation system) may be associated with migration and population expansion to areas with harsh climate (e.g., arid areas in Arizona and California). These demographic changes in turn causes larger population exposed to natural disasters and hence increase disaster damages. If this effect is sufficiently large, the overall impact of endogeneity may be ambiguous.

[22] The results of first stage regressions, given in Eq. (6), are reported in column 2 of Table C.14 and C.15.

Table 10: Patent counts in response to disaster damage in a state with the control function

	(1) Floods	(2) Droughts	(3) Earthquakes
D_{-it-1}	0.0588	0.206**	0.0179
	(0.0347)	(0.0684)	(0.0127)
D_{-it-2}	0.130***	0.0623	0.000270
	(0.0324)	(0.107)	(0.0157)
D_{-it-3}	0.0392	0.227***	0.00796
	(0.0453)	(0.0686)	(0.0127)
D_{-it-4}	0.0124	0.180*	0.0269**
	(0.0473)	(0.0773)	(0.0102)
D_{-it-5}	0.0701	0.224**	0.0178
	(0.0423)	(0.0803)	(0.0108)
Cumulative Effect	0.311**	0.900 ***	0.0708*
	(0.120)	(0.208)	(0.0346)
D_{it-1}	5.221	5.832	0.0406***
	(3.669)	(4.408)	(0.00986)
D_{it-2}	-0.152	0.104	0.0373***
	(0.634)	(0.179)	(0.0103)
D_{it-3}	0.351	-1.780	0.0257
	(0.377)	(0.990)	(0.0177)
D_{it-4}	-0.0420	0.270**	0.0271*
	(0.998)	(0.104)	(0.0116)
D_{it-5}	0.0768	-0.264	0.0851
	(0.578)	(0.296)	(0.106)
Cumulative Effect	5.455	4.161	0.216*
	(4.513)	(4.475)	(0.0994)
Real GDP per capita	0.0707	0.148*	-0.00741
	(0.0562)	(0.0616)	(0.0356)
Total patents	0.0278	-0.00297	-0.0711**
	(0.254)	(0.0410)	(0.0244)
R&D tax credits	4.507	11.93	7.969***
	(6.329)	(10.18)	(2.215)
Higher edu R&D exp	-0.303	-0.627	-0.0353
	(0.901)	(0.386)	(0.184)
post_1997	-1.597	-1.717	0.605
	(1.142)	(1.246)	(0.899)
Control function	-4.932	-5.321	-0.0619
	(2.581)	(4.439)	(0.110)
N	1392	1392	1479
States	48	48	51

Column 1 and 2 list results for 48 contiguous states since NCDC does not provide Palmer indices for Alaska, Hawaii and Washington D.C.; standard errors are presented in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

effects are positive and significant for all three types of disasters, and this suggests that innovation in a state is stimulated by disaster damage in the rest of the country. In other words, impact-reducing innovation is not localized to where disasters occur. The second cumulative effects presents the impact of local disaster damage on innovation in the next five years. The impact of local disaster damage on patents in a given state are all positive, but only significant in the case of earthquakes. In summary, for all three types of disasters, the response of innovation appears to be national, despite earthquake impact-reducing innovation tends to be more localized compared to innovation pertaining to floods and droughts.

7. Conclusion

Natural disasters cause significant casualties and damage worldwide every year. Moreover, climate change is expected to dramatically increase the frequency and intensity of natural disasters in the future. This paper presents a conceptual model where perceived risk theory and profit motive are combined to account for innovation activities induced by natural disasters. Using the U.S. patent data and natural disasters data from SHELDUS^{TM} for the years 1977-2005, the state-level empirical analysis on floods, droughts, and earthquakes reveals that impact-reducing innovation as a responds to natural disasters is not localized to where disasters occur, that is, disaster damage spurs innovation in both nearby and distant states. According to the empirical analysis, \$1 billion losses from flood events in the U.S. is predicted to stimulate a 35% increase in flood impact-reducing innovation in a state in the next five years. For droughts and earthquakes, \$1 billion losses is predicted to spur 173% and 20% more innovations respectively. Although disaster damage spurs innovation anywhere in the country, there is variation across disaster types: flood or drought damage in a state does not necessarily spur innovation in local areas, whereas in the case of earthquakes, there is a notable response of state-level innovation to local earthquake damage.

According to the framework introduced in this paper, disaster events raise self-protection needs of local communities and the demand for impact-reducing technology. As a result, profitability should motivate potential innovators across different states to develop impact-reducing technologies. Such innovation would be incentivized by profit and conducted by research groups with adequate research capacity. This explains the findings that innovation is not localized to where disasters occur. Nonetheless, for natural disasters like earthquakes, the expected market size and market value of impact-reducing technology is limited due to the nature of the disaster. Plus, local innovators have the advantage of obtaining first-hand information. All of these factors may contribute to an active response to local disaster events.

Impact-reducing innovations as proactive measures to adapt to natural disasters have potentially more profound impacts than reactive measures: they build adaptive capacity to disasters and reduce future disaster damage. However, historically, most government involvement in coping with natural disasters in the U.S. has been reactive, such as disaster relief fund and infrastructure rebuild. Recently, FEMA suggests a reform to promote investment in proactive measures and reduce disaster costs in the long-term. The proposed reform targets on its disaster spending on the Public Assistance (PA) funds: a disaster deductible will be established so that a state is required to spend up to its deductible before it is qualified to receive the PA funds. The deductible could be lowered for states that adopt certain impact-reducing practices. FEMA's proposal highlights the important role of the federal government in promoting proactive measures to adapt to natural disasters.

The findings presented in this paper have important implications for the public sector on how to motivate proactive measures such as disaster impact-reducing innovation. First, as natural disasters can result in impact-reducing innovations across states, R&D on impact-reducing technology should be distributed to both *local and remote* institutions and innovators with research capacity. The findings in this paper emphasize a proactive role for the federal government as the key to channelling and effectively spurring impact-reducing innovations nationwide. Second, the result that innovation is not localized to where disaster occur implies that profit is likely to be the main driver behind such innovations. The market for impact-reducing technologies, which relies on the private sector, is likely to be inefficient in providing disaster impact-reducing innovations. With positive externalities of innovations, private and social benefits diverge, and hence public support, such as R&D subsidy on impact-reducing technology, is crucial for achieving efficiency.

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APPENDIX:

Appendix A. Patent Search Criteria

"Flood" is a commonly used words in many disciplines and industries other than the natural disaster "flood" (e.g., printing, radiation imagery chemistry, and information security). Irrelevant patents can be excluded by restricting classes to search. Therefore, all search criteria for flood impact-reducing patents consist keywords and classes. Three criteria are established for flood (Table Appendix A): the main criterion for patents pertaining to floods, and also criterion 1 and 2. The use of "drought" and "earthquake" is much more specific to natural disasters, and hence restricting classes is not necessary. Patent counts calculated from each criteria are applied to Eq. (3) and (4) with Poisson FE model to check robustness, and results are reported in Table A.12. The results from criterion 1 and 2 are consistent with the finds using the main criteria. Patents pertaining to flood positively respond to national flood damage in the U.S. Additionally, there is no evidence that flood impact-reducing patents respond to local floods.

Table A.11: Patent Search Criteria for Floods, Droughts and Earthquakes

Disaster type	Classes	Keywords
Droughts	all	drought and one word in (tolerant tolerance resistant resisting resistance combat fight relief)
Earthquakes	all	earthquake
Floods		
Main criterion	52	flood
	114 (subclasses 230.15- 230.19, 263)	flood
	405 (subclasses 15-35, 73, 79, 80, 87-107, 109-117, 212-215, 218-221)	flood
	137, 206, 340, 702	flood control, flood detector, flood detection, flood preventer, flood prevention, flood preventing, prevents flood, prevent flood, prevention of flood, flood protection, flood damage, flood damages, flood relief, flood pump, flood alarm, flood warning, flood level, flood zone, flood risk, flood risks, flood free, flood barrier, flood disaster, flood resistant, flood water barrier, flood shield, flood threat, protecting structures from flooding water, prevent flooding water, prevent flood water
Criterion 1	52	flood
	114 (subclasses 230.15- 230.19, 263)	flood
	405 (subclasses 15- 35, 73, 79, 80, 87-107, 109-117, 212-215, 218-221)	flood
Criterion 2	52, 114, 405, 137, 206, 340, 702	flood control, flood detector, flood detection, flood preventer, flood prevention, flood preventing, prevents flood, prevent flood, prevention of flood, flood protection, flood damage, flood damages, flood relief, flood pump, flood alarm, flood warning, flood level, flood zone, flood risk, flood risks, flood free, flood barrier, flood disaster, flood resistant, flood water barrier, flood shield, flood threat, protecting structures from flooding water, prevent flooding water, prevent flood water

Table A.12: Patent counts in response to national and state-level flood damage

	(1) Criterion 1	(2) Criterion 2	(3) Main
D_{t-1}	0.116**	0.0756	0.0827*
	(0.0444)	(0.0448)	(0.0405)
D_{t-2}	0.152***	0.0971**	0.128***
	(0.0360)	(0.0334)	(0.0268)
D_{t-3}	0.00518	0.0546	0.0522*
	(0.0287)	(0.0297)	(0.0259)
D_{t-4}	-0.00182	0.0113	-0.0168
	(0.0565)	(0.0484)	(0.0480)
D_{t-5}	0.0296	0.0653*	0.0513
	(0.0452)	(0.0318)	(0.0317)
Cumulative Effect	0.301*	0.304**	0.297***
	(0.135)	(0.0897)	(0.0762)
GDP per capita	0.00121	-0.0313	0.00308
	(0.0319)	(0.0355)	(0.0270)
Total patents	0.0261	0.0154	0.0435
	(0.0630)	(0.0248)	(0.0411)
R&D tax credits	8.083	0.0928	5.730
	(5.978)	(0.201)	(4.937)
Higher edu R&D exp	-0.354	0.521***	-0.0852
	(0.474)	(0.155)	(0.282)
post_1997	0.520	0.435	0.0581
	(0.806)	(0.864)	(0.652)
N	696	841	899
States	24	29	31

The dependent variables in column (1)-(3) are patents pertaining to floods searched by criterion 1, 2 and the main criterion. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1) Criterion 1	(2) Criterion 2	(3) Main
D_{it-1}	0.538	0.423	0.474
	(0.291)	(0.226)	(0.254)
D_{it-2}	-0.282	-0.0240	-0.110
	(0.513)	(0.320)	(0.253)
D_{it-3}	0.271	0.378	0.333
	(0.273)	(0.217)	(0.213)
D_{it-4}	0.236	-0.199	0.0629
	(0.268)	(0.218)	(0.236)
D_{it-5}	0.238	0.0491	0.0298
	(0.308)	(0.341)	(0.301)
Cumulative Effect	1.001	0.626	0.789
	(0.958)	(0.572)	(0.588)
D_{-it-1}	0.0986*	0.0612	0.0627*
	(0.0390)	(0.0359)	(0.0293)
D_{-it-2}	0.155***	0.104**	0.133***
	(0.0368)	(0.0349)	(0.0268)
D_{-it-3}	0.00183	0.0434	0.0459
	(0.0278)	(0.0326)	(0.0278)
D_{-it-4}	-0.00133	0.0227	-0.0133
	(0.0573)	(0.0452)	(0.0471)
D_{-it-5}	0.0314	0.0640	0.0536
	(0.0438)	(0.0334)	(0.0320)
Cumulative Effect	0.285*	0.295**	0.281***
	(0.135)	(0.0909)	(0.0759)
Real GDP per capita	0.000564	-0.0302	0.00346
	(0.0314)	(0.0338)	(0.0266)
Total patents	0.00262	0.00423	0.0284
	(0.0784)	(0.0326)	(0.0519)
R&D tax credits	7.420	0.0904	5.154
	(6.048)	(0.162)	(5.023)
Higher edu R&D exp	-0.290	0.603***	0.00790
	(0.437)	(0.149)	(0.251)
post_1997	0.595	0.390	0.0588
	(0.785)	(0.813)	(0.637)
N	696	841	899
States	24	29	31

The dependent variables in column (1)-(3) are patents pertaining to floods searched by criterion 1, 2 and the main criterion. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.13: **Summary of variables at the state level**

States	Floods Patents	Floods Damage	Droughts Patents	Droughts Damage	Earthquakes Patents	Earthquakes Damage	Total patents	Real GDP per capita	R&D tax credits	Higher edu R&D expenditure
Alabama	0	2.576	0	0.343	1	0	0.382	21.441	0	0.361
Alaska	0	0.116	0	0.006	1	0.028	0.045	45.512	0	0.103
Arizona	0	0.858	1	0	3	0	1.287	22.236	0.075	0.399
Arkansas	0	0.502	1	1.122	0	0	0.158	19.887	0	0.107
California	17	4.708	7	0.004	210	43.968	14.089	28.12	0.057	3.428
Colorado	1	0.713	0	0.122	2	0	1.509	27.825	0	0.46
Connecticut	2	0.244	2	0	6	0	1.975	36.382	0.016	0.451
Delaware	0	0.051	2	0.041	0	0	0.523	37.511	0.002	0.068
District of Columbia	1	0.024	0	0	0	0	0.096	85.286	0	0.204
Florida	10	3.09	2	0.132	7	0	2.351	23.293	0	0.708
Georgia	2	0.768	0	0.568	4	0	1.157	26.365	0.028	0.747
Hawaii	0	0.283	1	0.001	12	0.015	0.083	31.226	0.041	0.133
Idaho	0	0.19	0	0.605	2	0.029	0.751	18.894	0.009	0.068
Illinois	6	5.473	4	0.37	8	0	3.714	30.751	0.003	1.045
Indiana	1	1.361	0	0.091	0	0	1.451	25.36	-1.277	0.442
Iowa	0	6.043	6	10.126	0	0	0.576	24.127	0.037	0.364
Kansas	0	1.172	3	0.187	0	0	0.406	25.376	0.003	0.209
Kentucky	4	1.604	0	0.306	1	0.003	0.457	23.588	0	0.207
Louisiana	11	1.341	1	0.811	0	0	0.487	27.589	0.008	0.347
Maine	1	1.108	0	0	1	0	0.15	22.647	0.001	0.048
Maryland	1	0.225	2	0.369	3	0	1.41	27.093	0.002	1.401
Massachusetts	2	0.239	2	0	5	0	3.39	31.617	0.052	1.416
Michigan	3	2.739	1	0	1	0	3.42	30.199	0	0.889
Minnesota	1	2.19	1	0.014	3	0	2.174	28.472	0.024	0.415
Mississippi	2	4.97	0	0.74	0	0	0.16	18.935	0	0.172
Missouri	1	3.153	5	0.025	3	0	0.893	26.443	0.002	0.495
Montana	0	0.065	1	0	0	0.001	0.114	20.112	0.012	0.08
Nebraska	1	0.803	1	1.01	0	0	0.201	25.423	0	0.187
Nevada	0	1.068	0	0	2	0	0.278	29.366	0	0.089
New Hampshire	1	0.066	0	0	3	0	0.622	25.438	0.008	0.128
New Jersey	6	2.018	3	0.122	9	0	4.154	33.002	0.041	0.481
New Mexico	0	0.125	0	0.024	1	0	0.3	22.917	0	0.236
New York	4	1.452	5	0.197	26	0	5.937	33.058	0	2.191
North Carolina	3	0.696	4	0.143	1	0	1.558	24.474	0.016	0.825
North Dakota	0	5.654	0	1.979	0	0	0.069	20.623	0.034	0.073
Ohio	1	1.379	2	0.28	11	0	3.28	27.784	0	0.789
Oklahoma	1	0.862	1	1.592	0	0	0.649	21.643	0	0.214
Oregon	0	0.312	2	0.032	4	0.012	1.216	21.162	0.028	0.302
Pennsylvania	3	2.109	1	1.967	12	0	3.678	26.075	0.003	1.337
Rhode Island	1	0.009	1	0	0	0	0.312	25.796	0.061	0.129
South Carolina	0	0.176	1	0.668	1	0	0.553	22.032	0.008	0.241
South Dakota	0	0.309	1	0.05	0	0	0.06	20.186	0	0.03
Tennessee	3	0.762	1	0	6	0	0.764	24.369	0	0.362
Texas	16	6.735	1	7.165	10	0	4.872	25.868	0.008	1.77
Utah	0	0.689	0	0	3	0	0.569	21.324	0.014	0.266
Vermont	0	0.414	0	0	0	0	0.315	22.374	0.001	0.068
Virginia	0	2.916	1	0.735	3	0	1.152	27.238	0	0.49
Washington	3	0.563	2	0.014	8	8.285	1.891	28.968	0	0.562
West Virginia	1	2.379	0	0.047	0	0	0.186	20.004	0.062	0.071
Wisconsin	3	2.588	0	0.821	3	0	1.658	25.767	0.026	0.602
Wyoming	0	0.1	0	0	0	0	0.057	27.816	0	0.043

The table reports sum for damage and patent counts for floods, droughts, and earthquakes. Total patents, Real GDP per capita, R&D tax credits, and Higher edu R&D expenditure are reported as mean from 1977 to 2005 for each state. Total patents is in thousand counts. Higher edu R&D expenditure is in billion dollars, and per capita real GDP is in thousand dollars. All dollar terms are adjusted to 2013.

Appendix B. Maps of Patents and Disaster Damage

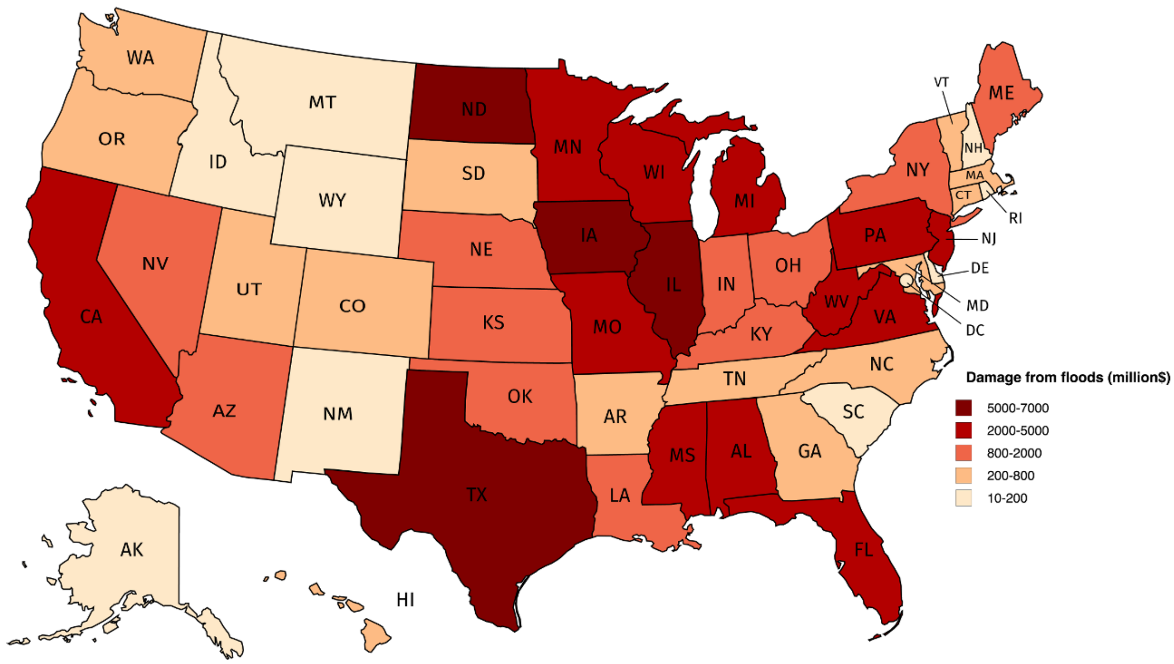

Figure B.1: Map of flood damage across states from 1977-2005

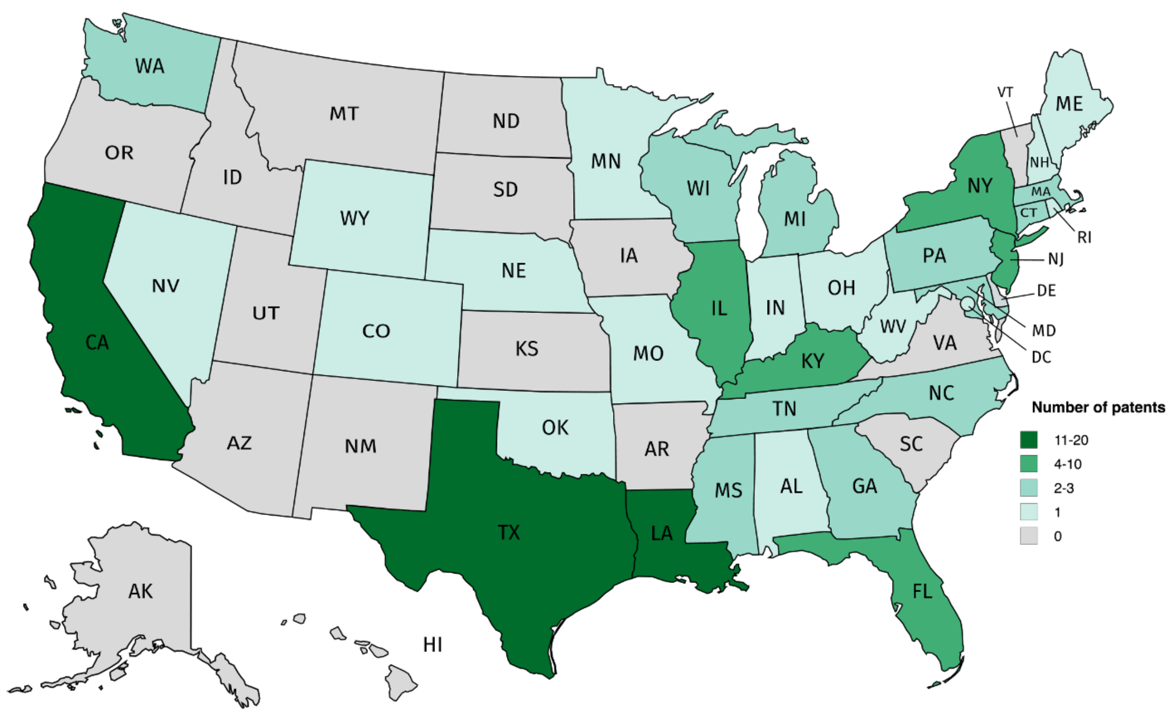

Figure B.2: Map of flood impact-reducing patents across states from 1977-2005

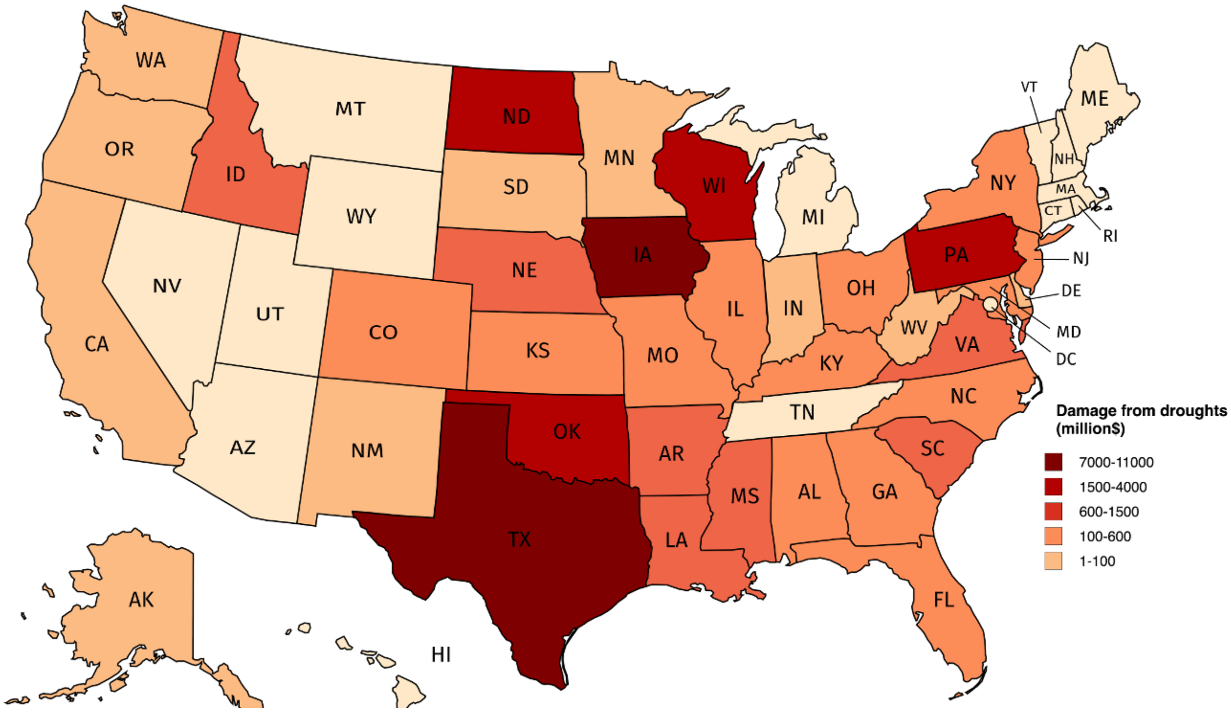

Figure B.3: Map of drought damage across states from 1977-2005

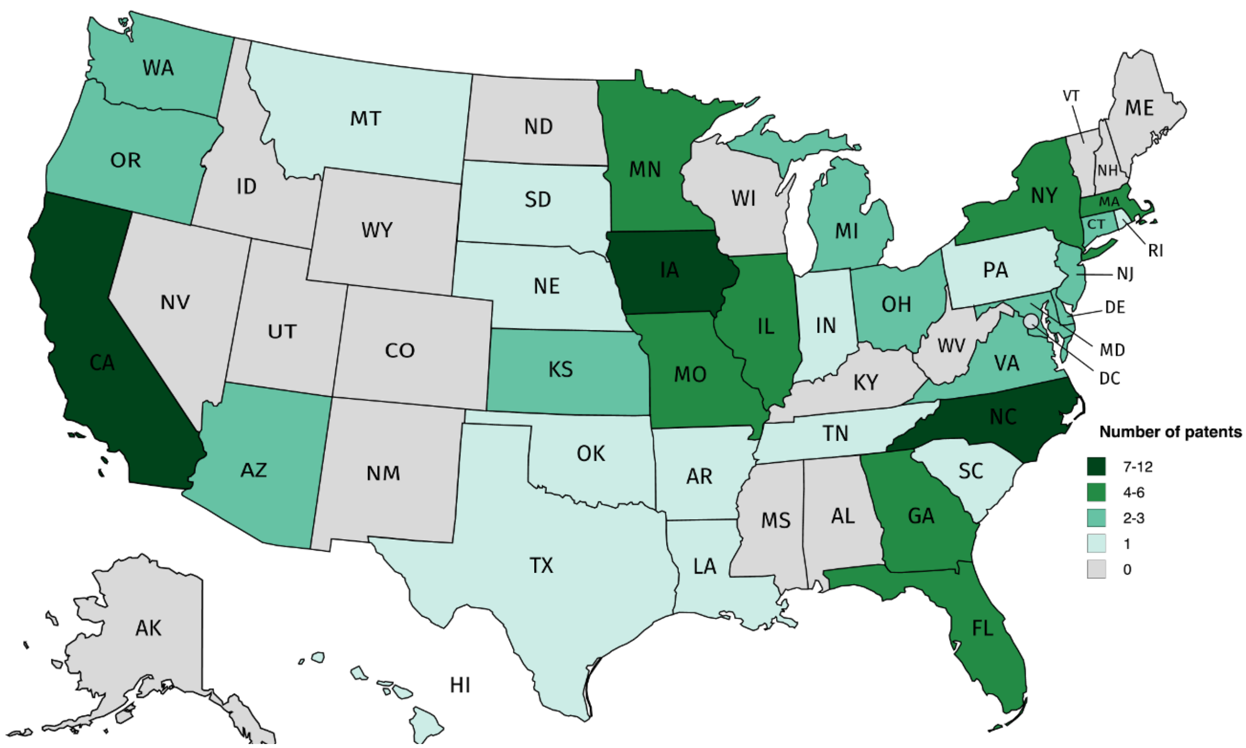

Figure B.4: Map of drought impact-reducing patents across states from 1977-2005

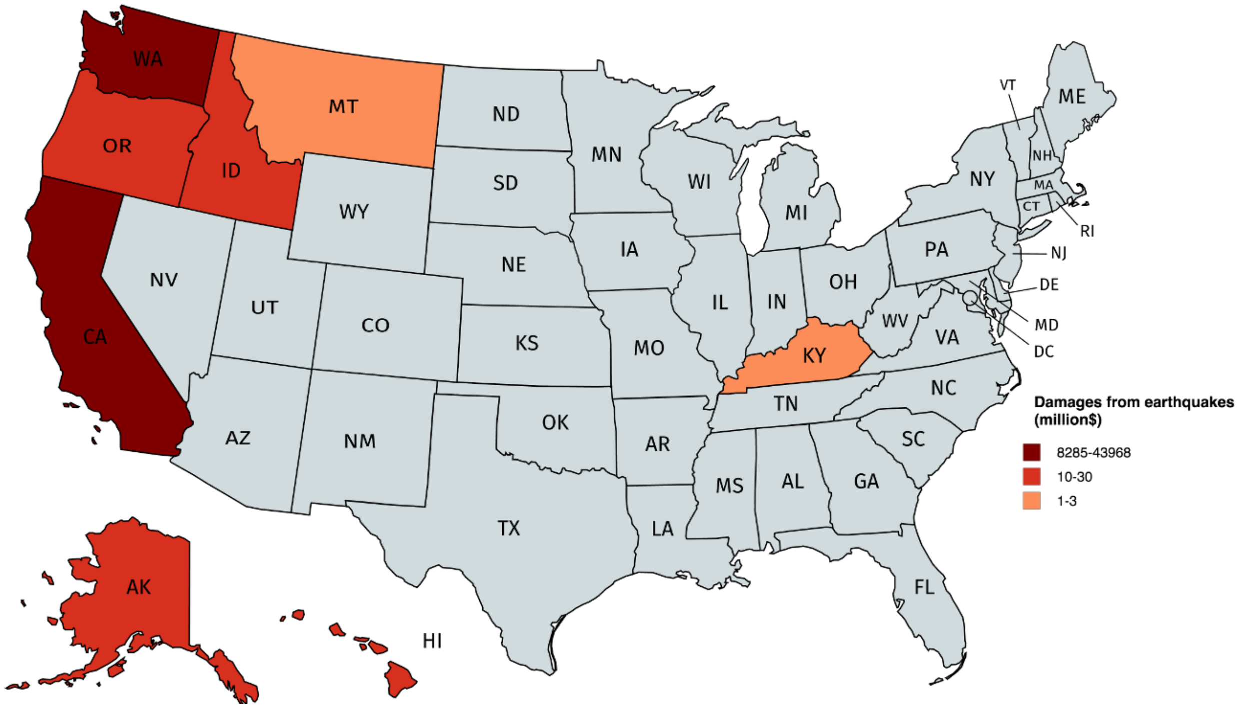

Figure B.5: Map of earthquake damage across states from 1977-2005

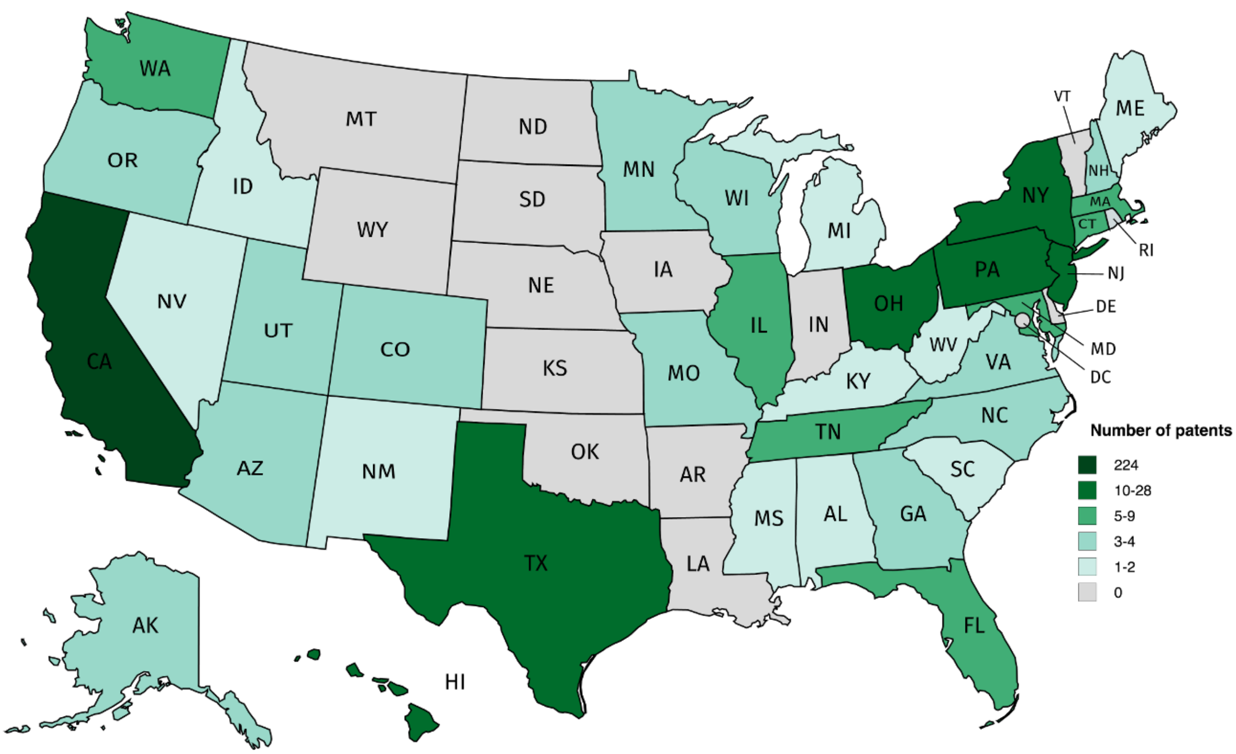

Figure B.6: Map of earthquake impact-reducing patents across states from 1977-2005

Appendix C. IV Tests and the Control Function Approach

Table C.14: Control functions for flood damage

	(1) National damage	(2) State damage
us_palmerz2_5	0.355***	
	(0.0551)	
us_maxpalmerz	0.534***	
	(0.0497)	
palmerz2_5		0.0218 *
		(0.0099)
maxpalmerz		0.0150 *
		(0.0077)
GDP per capita	-0.0112	-0.00141
	(0.0101)	(0.00251)
Total patents	0.0814	0.00882*
	(0.0660)	(0.00421)
R&D tax credits	0.0542***	0.00216**
	(0.0127)	(0.000748)
Higher edu R&D exp	-0.254	-0.00636
	(0.311)	(0.0277)
post_1997	1.736***	0.0446
	(0.335)	(0.0767)
N	1479	1392

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.15: Control functions for drought and earthquake damage

	(1) National damage	(2) State damage
us_pdsi3	0.294***	
	(0.00118)	
us_minpdsi	-0.0311***	
	(0.000813)	
pdsi3		0.00761*
		(0.00372)
minpdsi		-0.00757*
		(0.00342)
GDP per capita	0.0160**	-0.000583
	(0.00511)	(0.000927)
Total patents	-0.106***	-0.00172
	(0.0154)	(0.00311)
R&D tax credits	0.0263***	-0.000429
	(0.00121)	(0.000392)
Higher edu R&D exp	0.794***	0.0463
	(0.114)	(0.0256)
post_1997	-0.433***	0.00390
	(0.111)	(0.0244)
N	1479	1392

The dependent variables are drought damage.
Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	(1) National damage	(2) State damage
us_mag4_5	0.0120***	
	(0.000674)	
us_magmax	2.871***	
	(0.0213)	
mag4_5		0.0690***
		(0.00693)
magmax		0.00572 *
		(0.00205)
GDP per capita	-0.0386***	-0.000617
	(0.00918)	(0.00134)
Total patents	-0.154**	-0.0505
	(0.0529)	(0.0336)
R&D tax credits	0.0323***	0.00237
	(0.00458)	(0.00215)
Higher edu R&D exp	1.988***	0.299
	(0.321)	(0.259)
post_1997		-0.0374
		(0.0460)
N	1479	1479

The dependent variables are earthquake damage.
Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix D. Fatalities as a Measure of Disaster Damage

Impact-reducing patent applications respond to national aggregated fatalities. The results are reported in TableD.17. There is strong evidence that impact-reducing patent applications positively respond to national aggregate fatalities for floods and earthquakes. However, patents pertaining to droughts do not positively respond to drought fatalities due to a small number of fatalities from drought in the U.S.

Table D.16: Response of patents to national disaster fatalities

	(1) Floods	(2) Droughts	(3) Earthquakes
D_{it-1}	0.00777	-0.00192	0.0107**
	(0.00427)	(0.00950)	(0.00382)
D_{it-2}	0.00610**	-0.586	0.00784*
	(0.00215)	(0.388)	(0.00394)
D_{it-3}	0.00408	-0.0688*	0.00726
	(0.00426)	(0.0319)	(0.00374)
D_{it-4}	0.00390	0.00270	0.0134***
	(0.00396)	(0.00517)	(0.00339)
D_{it-5}	0.00304**	0.00146	0.0181***
	(0.000940)	(0.0131)	(0.00351)
D_{it-6}		0.00328	0.0160***
		(0.00950)	(0.00339)
D_{it-7}		-0.00195	0.0155***
		(0.00744)	(0.00337)
D_{it-8}		0.0710*	0.0112**
		(0.0330)	(0.00371)
D_{it-9}		0.0267***	0.00666
		(0.00522)	(0.00373)
Cumulative Effect	0.0249***	-0.528	0.106***
	(0.00713)	(0.349)	(0.0164)
Real GDP per capita	0.0144	0.0859	-0.0383
	(0.0324)	(0.0460)	(0.0297)
Total patents	0.0247	0.0653	-0.110***
	(0.0378)	(0.0712)	(0.0261)
R&D tax credits	7.191	1.596	6.658**
	(4.840)	(6.082)	(2.168)
Higher edu R&D exp	0.0900	-0.481	0.291
	(0.305)	(0.442)	(0.186)
post_1997	-0.130	-0.319	1.597*
	(0.769)	(1.058)	(0.749)
N	899	928	986
States	31	32	34

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D.17: Response of patents to fatalities from disasters in a state

	(1) Floods	(2) Earthquakes
D_{-it-1}	0.00790	0.00522
	(0.00431)	(0.00525)
D_{-it-2}	0.00649*	-0.00269
	(0.00284)	(0.00597)
D_{-it-3}	0.00491	0.00179
	(0.00433)	(0.00516)
D_{-it-4}	0.00489	0.0155***
	(0.00413)	(0.00451)
D_{-it-5}	0.00279**	0.0155***
	(0.000891)	(0.00458)
D_{-it-6}		0.0165***
		(0.00413)
D_{-it-7}		0.0185***
		(0.00412)
D_{-it-8}		0.0129**
		(0.00442)
D_{-it-9}		0.00510
		(0.00458)
Cumulative Effect	0.0270***	0.0882***
	(0.00838)	(0.0195)
D_{it-1}	0.0105	0.0156***
	(0.0183)	(0.00449)
D_{it-2}	-0.0128	0.0170***
	(0.0424)	(0.00439)
D_{it-3}	-0.0114	0.0134**
	(0.0173)	(0.00451)
D_{it-4}	-0.0247	0.0111*
	(0.0206)	(0.00481)
D_{it-5}	0.0182	0.0213***
	(0.0136)	(0.00471)
D_{it-6}		0.0137**
		(0.00501)
D_{it-7}		0.00895
		(0.00509)
D_{it-8}		0.00974
		(0.00545)
D_{it-9}		0.00944
		(0.00504)
Cumulative Effect	-0.0203	0.120***
	(0.0570)	(0.0214)
Real GDP per capita	0.0163	-0.0190
	(0.0354)	(0.0295)
Total patents	0.0450	-0.0918**
	(0.0372)	(0.0304)
R&D tax credits	5.480	5.836**
	(5.418)	(2.182)
Higher edu R&D exp	0.0727	0.150
	(0.305)	(0.202)
post_1997	-0.175	1.081
	(0.826)	(0.751)
N	899	986
States	31	34

Estimates for drought damage is not available due to small variation in the data; standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix E. Innovation in Response to the Regional Disaster Damage

This section examines the impact of disaster damage at a regional level that groups neighboring states. Many disaster events cause damage to multiple states that are geographically close to each other, and these states share similar disaster profiles and environmental characteristics. Hence, it is possible that the response of innovation to natural disaster is localized at a regional level. First, a disaster event in a state may increase perceived risks in nearby states and triggers rising demand of adaptive technology at the regional level. Moreover, a new impact-reducing technology in a state can be applied without altering cost to other nearby states as a result of the similar environmental characteristics. Lastly, if a type of disaster is location-specific, the potential market of adaptive technology is likely to be localized to nearby states that are vulnerable to the same type of disaster.

Here, the basic model (2) is extended to a region including a state and its neighboring states. Innovation in a given state is modeled as a function of regional disaster damage, controlling for other factors:

$$E\left[V_{jit}|D,X\right] = exp\left(\sum_{k=1}^{m}\beta_k D^n_{jit-k} + \sum_{k=1}^{m}\gamma_k D^o_{jit-k} + \mu X_{it,t-1} + \eta_i\right), \tag{E.1}$$

where D^n_{jit-k} is damage from disaster type j in state i and its neighbouring states in year $t-n$, and D^o_{jit-k} is damage from disaster type j in the rest of the U.S. (excluding the state i and its neighboring states) in year $t-k$.

Eq. (E.1) is estimated with the Poisson FE model, and the results for floods, droughts and earthquakes are reported in Table E.18. For droughts and floods, there is no evidence that impact-reducing patents respond to disaster damages in the neighboring states, whereas the cumulative effects of disaster damage in non-bordering states are positive and significant. This result further enhances the previous finding that the response of impact-reducing innovations is national in scope for floods and droughts. For earthquakes, the cumulative effect of aggregate damage from the nearby states is positive and significant, in contrast to the insignificant impacts of damage in non-bordering states. Combining previous findings, the response of earthquake impact-reducing innovations is mostly localized to the nearby region of an earthquake event.

Appendix F. GMM IV methods

Several moment-based methods have been developed for count data to deal with weakly exogeneity and endogeneity. Two-step generalized method of moments (GMM) estimators with instrumental variables (IVs) are available for cross-section data, depending on whether the error term is additive (Grogger, 1990), or multiplicative (Mullahy, 1997). Windmeijer and Santos Silva (1997) provide comparison the two estimators. For panel count data, the methods of moments in use rely on functional form assumptions and are quite limited. Chamberlain (1992) and Wooldridge (1997) propose moment conditions with quasi-differencing transformations, which allow for consistent estimation in panel count data with weakly exogenous regressors. Windmeijer (2000) shows that their transformation is also appropriate for endogenous regressors, and suggests an alternative transformation where deviation of the overall mean of covariates is incorporated in the moment condition, so that the moment estimator can be applied to nonnegative right hand side variables. The above GMM estimators have been applied to many studies (Blundell et al., 2002; Miao and Popp, 2014; Hovhannisyan and Keller, 2015).

However, one major drawback of GMM estimators is computational complexity, and availability of estimates is subject to variation in the data and model complexity, which is the case in this study. First, the relatively large number of zeros in the dependent variable for patents in a state appears to make it computationally difficult to exploit the moment conditions that this estimator relies on. Second,

Table E.18: Patent counts in response to regional disaster damage

	(1) Floods	(2) Droughts	(3) Earthquakes
D^n_{it-1}	0.236***	0.338***	0.0404***
	(0.0617)	(0.0963)	(0.00551)
D^n_{it-2}	0.114	0.0795	0.0384***
	(0.0859)	(0.164)	(0.00528)
D^n_{it-3}	0.127	0.120	0.0252*
	(0.0827)	(0.125)	(0.0103)
D^n_{it-4}	-0.323	0.303**	0.0284***
	(0.255)	(0.0924)	(0.00429)
D^n_{it-5}	-0.125	-0.249	0.0261***
	(0.156)	(0.275)	(0.00491)
Cumulative Effect	-0.0490	0.592	0.158***
	(0.388)	(0.374)	(0.0210)
D^o_{it-1}	0.0543	0.263***	0.0201
	(0.0362)	(0.0780)	(0.0141)
D^o_{it-2}	0.134***	0.0888	-0.000889
	(0.0243)	(0.114)	(0.0286)
D^o_{it-3}	0.0460	0.235**	0.00952
	(0.0309)	(0.0728)	(0.0135)
D^o_{it-4}	0.000813	0.152	0.0213
	(0.0468)	(0.0963)	(0.0140)
D^o_{it-5}	0.0736*	0.265***	0.0154
	(0.0336)	(0.0802)	(0.0106)
Cumulative Effect	0.306***	1.004***	0.0655
	(0.0712)	(0.200)	(0.0424)
GDP per capita	0.00107	0.153*	-0.0302
	(0.0258)	(0.0596)	(0.0429)
Total patents	0.0556	0.00732	-0.0765**
	(0.0537)	(0.0363)	(0.0258)
R&D tax credits	5.064	2.461	7.466*
	(4.907)	(6.152)	(3.436)
Higher edu R&D exp	-0.0660	-0.243	0.0328
	(0.306)	(0.271)	(0.145)
post_1997	0.0767	-1.901	1.236
	(0.633)	(1.196)	(1.145)
N	899	928	986
States	31	32	34

All columns are estimates with the Poisson FE method; standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

for a distributed lag model like Eq.(3) and (4), the moment condition contains information of lags of endogenous variables and lags of all IVs. For instance, five-year lags of flood damage is accompanied by five-year lags of the two IVs for flood, the total number of ten IVs. This dramatically increase computational complexity, and more importantly, reduce validity of IVs (disaster intensity in year s almost have no correlation with disaster damage in year t , for $t \neq s$). As a result, many of the above GMM IV estimators are not convergent with Eq.(3) and (4). Table F.19 reports available estimates on national flood, drought, and earthquake damage. The overall results support the finding that innovation in a state responds to natural disasters.

Table F.19: Response of patents to national disaster damage

	(1)	(2)	(3)
	Floods	Droughts	Earthquakes
	Grogger(1990)	Windmeijer(2000)	Windmeijer(2000)
D_{t-1}	0.0568	0.211*	0.0439
	(0.0624)	(0.0955)	(0.0435)
D_{t-2}	0.109*	0.162	0.0695*
	(0.0456)	(0.105)	(0.0340)
D_{t-3}	0.0931	0.0491	0.00988
	(0.0523)	(0.111)	(0.0347)
D_{t-4}	-0.0219	0.236	
	(0.0655)	(0.185)	
D_{t-5}	0.0441	0.539	
	(0.0424)	(0.363)	
Cumulative Effect	0.345*	1.196**	0.123*
	(0.0163)	(0.415)	(0.0605)
GDP per capita	-0.00206	0.0483**	-0.0489*
	(0.0336)	(0.0156)	(0.0239)
Total patents	0.0363	-0.0294	0.164
	(0.110)	(0.0666)	(0.120)
R&D tax credits	7.452		
	(33.53)		
Higher edu R&D exp	-0.100		
	(0.411)		
post_1997	0.208		
	(0.712)		
N	1479	1479	1479

Column 1 reports estimates for floods with the GMM IV method proposed by Grogger(1990) with state fixed effects; estimates in column 2 and 3 are based on the GMM IV estimator for panel fixed effect by Windmeijer (2000); GDP per capita and total patents are control variables n column 2 and 3; standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$