Journal of Environmental Economics and Management 68 (2014) 280–295

Contents lists available at ScienceDirect

Journal of
Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Necessity as the mother of invention: Innovative responses to natural disasters

Qing Miao [a,*], David Popp [a,b,1]

[a] Department of Public Administration and International Affairs, Center for Policy Research, The Maxwell School, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244-1020, USA
[b] National Bureau of Economic Research, USA

ARTICLE INFO

Article history:
Received 17 June 2013
Available online 23 June 2014

JEL classification:
O3
Q54
Q55

Keywords:
Natural disasters
Climate change adaptation
Induced innovation
Risk perception
Knowledge stocks
Earthquakes
Droughts
Floods

ABSTRACT

How do innovators respond to the shock of a natural disaster? Do natural disasters spur technical innovations that can reduce the risk of future hazards? This paper examines the impact of three types of natural disasters—floods, droughts and earthquakes—on the innovation of their respective mitigation technologies. Using patent and disaster data, our study is the first to empirically examine adaptation responses across multiple sectors at the country level. Considering the potential endogeneity of disaster damages, we use meteorological and geophysical data to create hazard intensity measures as instrumental variables. Overall, we show that natural disasters lead to more risk-mitigating innovations, while the degree of influence varies across different types of disasters and technologies.

Introduction

How people cope with natural disasters is of interest to both policy makers and researchers. This issue presently is gaining renewed attention because of the increasingly evident threats of climate change. As climate scientists warn that global warming will likely increase the frequency and intensity of extreme weather events (e.g., floods, droughts, tropical cyclones and heat waves), incorporating strategies for reducing the risk of natural disasters is an important part of climate change adaptation (International Panel on Climate Change, 2012).[2]

In this paper, we ask whether natural disasters lead to innovations of risk-mitigating technologies. Such technologies are analogous to those that may aid adaptation to climate change and associated natural disasters. Specifically, we coin the term "risk-mitigating innovation," referring to the *development of new and more effective technologies that assist people in better*

* Corresponding author.
E-mail addresses: qmiao@syr.edu (Q. Miao), dcpopp@maxwell.syr.edu (D. Popp).
URL: http://faculty.maxwell.syr.edu/dcpopp/index.html (D. Popp).
[1] Fax: +1 315 443 1075.
[2] A term initially used to explain biological evolution, adaptation is now applied more often to human society and regarded as an important strategy to address climate change (for a review on the concept, see Smit and Wandel, 2006). The IPCC defines adaptation as "*adjustment in natural or human system in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities*" (IPCC, 2001: 72).

http://dx.doi.org/10.1016/j.jeem.2014.06.003
0095-0696/

coping with natural disasters and building resilience to future shocks. Such innovation may include both the development of new products and the improvement and commercialization of existing technologies to make them more appealing for consumers to adopt. Technological innovation is an important form of adaptation because it provides the necessary tools for people to utilize in adapting to a changing environment. Although adaptation in some cases can be just behavioral changes (e.g., relocation), people more often have to employ certain technologies, which take either a hard form (e.g., equipment and infrastructure such as building levees) or a soft form (e.g., science, technical know-how and skills such as emergency management) (UNFCC, 2006). Technological innovation enhances their capacity to cope with natural hazards and provides a long-term adaptation strategy.

As an example of how technology can affect adaptation, consider how the advent of air conditioning changed the development of regions in warmer climates. Moving forward, other innovations, such as developing new breeds of crops more resistant to drought, have the potential to adapt agriculture to possible future changes in climate. Smithers and Blay-Palmer (2001) discuss the role of technology research and development in agricultural adaptation, recognizing climate as an inducement for innovation. Increased attention recently has been paid to the implication of science and technology development in the policy world of climate adaptation, both domestically and internationally (e.g., UNISDR, 2009; UNFCC, 2006). In an editorial comment, Smith et al. (2009) suggest technology development and diffusion should be incorporated as a necessary component of the national adaptation architecture, given its role in "*expand(ing) the range of adaptation possibilities by expanding opportunities or reducing costs.*"

In this research, we take a worldwide view in investigating how innovation, as an economic and scientific endeavor, responds to the shock of natural disasters. By using risk-mitigating innovations as an outcome of adaptation, our study presents the first attempt to examine systematically adaptation responses across multiple sectors at the country level. In particular, we focus on three types of natural disasters—floods, droughts and earthquakes—and match each of them with one mitigation technology including flood control, drought-resistant crops and quake-proof buildings.[3] Our empirical analysis, using a panel of up to 28 countries over a period of 25 years, shows all three types of natural disasters have a significant and positive impact on the patent counts of their corresponding technologies. This result implies that the private sector is adapting by innovating, but in a more reactive than proactive manner.[4] It thus suggests government has a particularly important role to play in developing technologies necessary for mitigating risks so they are in place before a disaster occurs. In addition, we also explore whether domestic innovation is spurred by foreign disasters, and find such evidence in the case of floods.

Another contribution of this paper is to explore the motivation and ability for adaptation responses, which is an under-researched issue in the adaptation literature. Notably, a majority of the current adaptation studies focuses on estimating costs or cost-effectiveness of adaptation measures, and many climate models simply treat adaptation as autonomous. For instance, recent examples of climate policy models incorporating adaptation are the AD-DICE model (de Bruin et al., 2009), the WITCH model (Bosello et al., 2009), which assesses the optimal mix of mitigation and adaptation measures, and the FUND model, which has been used to analyze the tradeoff between mitigation and adaptation for protecting coastlines (Tol, 2007). None of these models consider the possibility that the tendency and ability to adapt are endogenous. Our empirical evidence of reactive risk-mitigating innovations can inform the current endeavors in integrated assessment modeling of climate change, and more specifically, suggests the possibility of treating adaptation as a function of previous disaster losses.

Finally, our study also contributes to the empirical literature on the economics of natural disasters by addressing the potential endogeneity of disaster damage. While the severity of disaster damages are a driver of risk-mitigating innovations, we argue that observed human and monetary losses experienced by a country from natural disasters are endogenous. We thus take an instrumental variable approach and use objective meteorological and geophysical data to exploit the exogenous variation in physical disaster intensity. Our measures of hazard magnitude are highly predictive of disaster damages experienced by our sample countries. This approach not only sheds light on research of the economic impacts of natural disasters, but also inform modeling of disaster losses, particularly with respect to controlling for exogenous natural hazards.

Relevant literature

This paper is part of a growing literature on the economics of natural disasters (for a survey of the literature, see Cavallo and Noy, 2010; Kellenberg and Mobarak, 2011). This literature consists of two bodies of research that are highly related but differ regarding the treatment of disaster variables: one concerning the economic effects of natural disasters, and the other assessing the determinants of natural disaster impacts. While this study falls into the former category by considering how natural disasters affect innovation, we also draw on the latter research to address the endogeneity of disaster damages. We

[3] It should be noted that earthquake is normally classified as a geological hazard and regarded with a weak link to climate change. However, given that catastrophic climate impacts have not yet been observed, we consider not only disasters directly relevant for climate change such as drought and floods, but also include responses to other natural disasters like earthquakes. Moreover, as researchers expect the probabilities of earthquakes to rise in certain regions (such as California) because of the crust movement, we believe earthquake fits neatly into the context of adaptation.

[4] The adaptation literature distinguishes between reactive adaptation and proactive adaptation (Fankhauser et al., 1999). The former occurs when people anticipate the risks and take measures to forestall disasters or mitigate their risks, while the latter refers to actions taken only after a disaster happens.

discuss the relevant literature on the determinants of natural disaster impacts while developing our conceptual framework in the next section.

With respect to the economic effects of natural disasters, the majority of empirical studies focus on how natural disasters affect economic growth using macroeconomic or sector-specific measures (e.g., Benson and Clay, 2004; Skidmore and Toya, 2002). A subset of research in this line looks into the behavioral changes induced by natural disasters. Cuaresma et al. (2008) examine how catastrophic risks affect the opportunity of technology transfer and capital updating, and document a negative effect of disaster frequency on knowledge spillovers to the affected developing countries.[5] Yang (2008a) uses meteorological data to investigate the impact of hurricanes on multiple types of financial flows, including foreign aid, lending and migrants' remittance, to the affected countries. At a more micro-level, recent papers have examined the impact of natural disasters on migration decisions (Paxson and Rouse, 2008; Yang, 2008b; Boustan et al., 2012), fertility and human capital investment (Baez et al., 2010; Finlay, 2009), risk attitudes and risk-taking behaviors (Callen, 2011; Cassar et al., 2011; Cameron and Shah, 2013).

Our research question also draws on the hypothesis of induced innovation, which posits that changes in the relative price of an input of production lead to innovations that enable reducing the use of the relatively more expensive factors (Hicks, 1932). Over the past decade, this theory has been examined by environmental economists to understand the relationship between energy prices, environmental regulations and innovations of environmental technologies (for an overview of this topic see Popp et al., 2010). Using U.S. patent data from 1970 to 1994, Popp (2002) finds that both demand-side influences (e.g. energy prices) and supply-side influences (e.g., the existing knowledge base) determine energy-efficient innovations. Similar empirical evidence on the responsiveness of innovations to energy prices and environmental regulations has been found by other researchers using other modeling techniques (e.g., Newell et al., 1999) and conducting cross-national analyses (e.g., Johnstone et al., 2010; Verdolini and Galeotti, 2011).

As climate change unfolds, there has been an increased recognition that climatic conditions may serve as a stimulus for technological innovation, particularly in the agricultural sector (Rodima-Taylor et al., 2011; Easterling, 1996; Koppel, 1995). One recent study of particular relevance is Chhetri and Easterling (2010) investigating how farmers in Nepal develop location-specific technologies in response to different local climatic constraints. As evidence of technological change, they demonstrate convergence in the productivity of rice crops in Nepal from 1991 to 2003, suggesting that more favorable technologies spread throughout Nepal agriculture in this time frame. They use qualitative methods to explain these changes, finding evidence that drought-tolerant breeds of rice were adopted in climatically marginal regions. Our study further extends this line of research by using a cross-country sample with specific measures of innovation and considering the shocks of natural hazards as an inducement for innovation.

Modeling

Conceptual framework

To understand the mechanism through which natural disasters spur risk-mitigating innovations, we propose a conceptual framework positing that the impact of a disaster shock raises the perceived risks and creates a higher demand for adaptive technologies. The anticipation of higher demand motivates the private sector to develop newer and more cost-effective technologies for mitigating future disaster risks. In essence, the key question is whether experiencing a disaster shock provides new information to update people's risk perception, given the known riskiness of the environment they are exposed to.

We begin by examining the perceived risk as an important mediating factor on the demand side that motivates risk-mitigating innovations. The theory of protection motivation (Rogers, 1983; Rogers and Prentice-Dunn, 1997) proposes that individuals' risk perception and perceived efficacy play a key role in affecting their self-protection decisions.[6] This theory recently has been applied to studying natural hazard preparedness and climate change adaptation (Grothmann and Patt, 2005; Martin et al., 2009; Mulilis and Lippa, 1990). Meanwhile, the disaster literature consistently suggests risk perception is affected by the prior disaster experiences and, particularly, the severity of damages realized (e.g., Weinstein, 1989; Perry and Lindell, 1986). In a recent study using experiment data in Indonesia, Cameron and Shah (2013) find that individuals who recently have experienced a disaster exhibit high levels of risk aversion, even after controlling for the frequency of natural hazards in the long term.

Drawing on this line of research, we model the unobserved perceived risk (R_{it}) as a function of the recent shocks country i has experienced, indicated by a distributed lag of disaster damages (D), a country's capacity to cope with and adapt to natural disasters (C_{it}), and the country's baseline hazard (H_i) (e.g., does the country have a fault line?). Based on the risk

[5] Although Cuaresma et al. (2008) also focus on the link between natural disasters and technology, their research question is fundamentally different from ours. While their study asks whether natural disasters make developing countries more likely to import and absorb new technologies to improve their productivity, our focus is on a specific group of technologies that can mitigate the risks of natural disasters.

[6] More specifically, the protection motivation theory discusses four cognitive factors falling on two dimensions: risk appraisal includes the perceived severity of threatening events and the perceived probability of the occurrence, while the perceived efficacy includes the efficacy of the protective measures and the perceived self-efficacy in coping with a threat. The empirical research, such as Grothmann and Patt (2005), draws on this theory to examine the cognitive factors that influence people's adaptive behavior.

perception literature surveyed above, we expect risk perceptions to depend on the severity of disaster damages (e.g., human and economic losses from natural disasters) rather than the frequency or magnitude of such events.[7]

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

The baseline hazard is important for perceived risk, because people living in a region known to be at risk for certain hazards are more likely to possess some level of risk perception. For example, 81 percent of all earthquakes occur in countries located along the "Ring of Fire" in the Pacific Ocean.[8] People living in these quake-prone regions might perceive a stronger risk of earthquakes.[9] Adaptive capacity may affect the perceived risk in different channels: first, previous investments to reduce vulnerability, such as sea walls or earthquake-resistant buildings, reduce the risk of significant damages following a disaster event. In such cases, the perceived need for additional innovation will be lower. Also, perceiving a strong adaptive capacity may cause over-confidence and then lower the perceived risks.[10]

Eq. (1) raises two additional conceptual issues: first, adaptive capacity is unobserved and often related to national attributes; and second, a country's adaptive capacity also influences the impact of a disaster shock it has experienced. To illustrate this further, we draw on the natural hazards and vulnerability literature, which suggests the actual disaster impact depends on both the physical severity of the hazard and local vulnerability or adaptive capacity (Yohe and Tol, 2002; Brooks et al., 2005; IPCC, 2012), with the latter being socially determined and place based. In other words, the same natural hazard occurring in different places will result in different impacts because some people and communities are more susceptible to hazards than others (Kousky, 2012; Cutter et al., 2003).

In line with the notion of vulnerability and adaptive capacity is a series of empirical studies examining the determinants of natural disaster impacts. Using a cross-national, multi-hazard data set, Kahn (2005) shows that nations with higher income and more democratic institutions suffer fewer deaths from natural disasters. He argues that economic development and good institutions lead to better infrastructure and preventive technologies, as well as more effective regulations and emergency management, which provide "implicit insurance" against natural disasters. Subsequent studies have examined a variety of institutional measures, including inequality (Anbarci et al., 2005), corruption (Escaleras et al., 2006), political regime (Keefer et al., 2011) and governance (Ferreira et al., 2013) as well as different patterns of the damage–income relationship (Toya and Skidmore, 2007; Raschky, 2008; Kellenberg and Mobarak, 2008; Schumacher and Strobl, 2011; Hallegatte, 2012) to account for cross-national heterogeneity in the disaster fatalities. Based on this literature, we model disaster impact (D_{it}) as a function of the physical magnitude of disaster shocks (M_{it}) and the country's adaptive capacity (C_{it}):

$$D_{it} = f(M_{it}, C_{it}) \tag{2}$$

We model a country's adaptive capacity as a function of its income (Y_{it}), quality of institutions (I_{it}) and existing knowledge stocks the country has obtained (K_{it-1}):

$$C_{it} = f(Y_{it},\ I_{it},\ K_{i,t-1}) \tag{3}$$

While income and institutions have been widely suggested as essential elements of adaptive capacity in the literature, an innovation of this paper is the inclusion of knowledge stocks, which represent the current technologies available to cope with disasters. The implication of including knowledge stocks in the model is that adaption is a dynamic process. Countries learn from their prior exposure to disasters and produce new knowledge that enables them to better adapt to future disaster risks. To the extent that previous events lead to new innovations, there will be less need for additional innovations after a subsequent shock.

Finally, innovation itself depends on the perceived risk (R_{it}), a country's existing knowledge base ($K_{i,t-1}$), income (Y_{it}), and science base (S_{it}):

$$PAT_{it} = f(R_{it},\ K_{it-1},\ Y_{it},\ S_{it}) \tag{4}$$

In the empirical analysis, we use the count of patent applications pertaining to a given technology (PAT_{it}) to measure the outcome of innovative activities. A country's science base includes the availability of qualified engineers to work on disaster-related research and patent policy, which determines the likelihood that inventors will seek patent protection for new innovations. We control for these by using the total number of patents by country and year.

Combining Eqs. (1), (3) and (4) to remove unobserved risk and capacity provides the following relationship:

$$PAT_{it} = f(\sum_{n=0}^{N} D_{it-n}, H_i,\ K_{it-1},\ Y_{it},\ I_{it,}S_{it}) \tag{5}$$

[7] The rationale is simple: if a natural disaster of an extremely high magnitude occurs in an uninhabited area and results in little damage, it may not substantially affect people's risk perception.

[8] http://earthquake.usgs.gov/learn/faq/?faqID=95, accessed April 24, 2012.

[9] However, some psychological and cultural studies suggest communities that have been long exposed to a certain natural hazard may have accepted it as part of their life and have a lower level of risk perception. So the direction of influence might go in both directions.

[10] An analogy is the theory of "levee effect" (Stefanovic, 2003), which posits that people may excessively rely on the existing protective measures knowing their existence. For example, people may think the construction of levees can fully protect themselves against all future floods.

Three issues are important to note regarding the final model. First, we consider multiple-year lags between disaster events and patents, not only because the perceived risks are affected by disaster damages that have occurred in recent years but also because innovation is a gradual process. Research projects take multiple years and staff may not be easily shifted to a new project just because a new profitable opportunity arises. Similarly, adjustments to perceived risk may also be gradual. For example, a drought in one year may be perceived as a random event. Persistent drought over multiple years may be perceived as a changing climate. As such, we consider multiple-year lags when estimating our model.

Second, although we expect a positive relationship between disaster damages and innovations, the effect of variables measuring adaptive capacity are ambiguous. Eqs. (1)–(3) suggest that both a greater existing knowledge stock and higher income increase adaptive capacity, thus reducing the perceived risks and also the need for additional innovations.[11] At the same time, Eq. (4) suggests existing knowledge serves as a building block for future innovations. Although the existing knowledge may inspire more innovations, it may also be the case that a strong existing stock may constrain technological opportunities and make future breakthroughs more difficult. Similarly, because innovation is primarily carried out in industrialized countries, and people from higher-income countries may have a higher demand for risk-mitigating technologies, a positive correlation between income and patenting activity is also possible.

Finally, Eq. (2) suggests that the observed damages experienced by a country are simultaneously determined by both the physical magnitude of the disasters and the country's adaptive capacity. As capacity is unobserved, but is a function of income, institution and existing knowledge, the resulting damages are thus endogenous. Nonetheless, our theory posits that disasters have their effect on risk perceptions via the damages they cause. Therefore, damages from recent natural disasters remain the key variable of interest in our conceptual and empirical model. In the following section we discuss how we address the endogeneity issue in our empirical work.

Empirical model

Based on the proposed conceptual framework, we use the model below for examining the relationship between disaster shocks and risk-mitigating innovations:

$$PAT_{jit} = f\left(\sum_{n=0}^{n_j} D_{it-n},\ Y_{it},\ I_{it},\ K_{jit-1},\ S_{it},\ \eta_i,\ \theta_t\right) \tag{6}$$

As the dependent variable, innovation (PAT_{jit}) is measured by the total number of successful patents in the technology field j applied for by the residents in country i in year t. It is the function of contemporaneous and lagged impacts of natural disasters that occurred in country i in the current year and up to n_j years before (the length of lag n_j is technology-specific) and a set of country characteristics including real GDP per capita (Y_{it}), political institutions (I_{it}), the existing domestic knowledge stock pertaining to the specific type of technology in question (K_{jit-1}) and the total patent applications by a country's residents (S_{it}). As discussed above, we use a distributed lag of disaster impacts given that the adaptation response takes time. We are reluctant to impose a structure on the effects of recent years' disasters on innovation because whether the most recent disasters have a bigger impact on innovative activities is an empirical question.

Country fixed effects (η_i) control for the unobserved time-invariant heterogeneity across country (e.g., the baseline hazard, risk-related norms and culture). By controlling for the country individual effects we are able to test whether disaster shocks add new information to the background risk, providing an impetus to adaptation and innovation. Year fixed effects (θ_t) control for the time-varying factors common to all countries (e.g., global technology advancement, salient disaster shocks occurring in one country that may affect the global risk perception).[12]

Given the count-data nature of our dependent variable (i.e., patent counts) and panel nature of our data, we use a Poisson fixed-effects model with robust standard errors to address possible over-dispersion in the data (Cameron and Trivedi, 2005).[13] Standard errors are clustered by country. We use the fixed-effects model because the unobserved heterogeneity across countries is very likely to exist and correlate with the explanatory variables.[14] The model is estimated using the Generalized Methods of Moments (GMM) technique (Hansen, 1982).

However, estimating this model raises two endogeneity concerns. First, as discussed earlier, the damages a country suffers from disasters are potentially endogenous to its socio-economic status. Although the country fixed effects control for the time-invariant characteristics, they cannot account for those time-varying elements of a country's adaptive capacity that may affect disaster outcomes and innovation responses simultaneously. The latter would cause omitted variable bias for our disaster variables and presumably lead the estimated effect of disaster damages on innovation to be negatively biased.

[11] It should also be noted that the relationship between income and disaster outcomes might be ambiguous when damages are measured as monetary loss. Compared to poor countries, rich countries tend to suffer higher economic damages from natural disasters because of their more expensive capital stocks and higher capital density (IPCC, 2012).

[12] The impact of the Fukushima nuclear disaster on preferences for nuclear power around the world provides an example of how large natural disasters can affect global risk perception.

[13] Because of the panel nature of the data, we do not use a negative binomial model, because the negative binomial fixed effect model does not truly control for unobserved fixed effects (Allison and Waterman, 2002; Cameron and Trivedi, 2005; Paulo, 2008).

[14] Unless we can find proper measures for the country specific heterogeneity and include them in the regression, the potential correlation between the observed fixed components η_i with the other regressors would make a standard random effects estimator inconsistent.

Second, our lagged knowledge stock variable is also endogenous, as it is, in part, simultaneously determined by the lagged damages included in our model.

To correct for endogeneity, we use variables that measure the physical disaster intensity to instrument for both disaster impact and knowledge stock variables.[15] Our argument for using the disaster magnitude as instruments is that they reflect the exogenous natural destructive power of a hazard, which directly affects the level of damages. Moreover, because our theory posits that disasters spur innovations and subsequent accumulation of the specific risk-mitigating knowledge, the physical intensity of previous disaster events should presumably exert a positive effect on the knowledge stocks. In other words, countries exposed to a hazard should possess more knowledge/technologies related to coping with this specific hazard. The instrumental variables used for each type of disaster are discussed in more detail in the data section.

Data

In this study we create a balanced panel of up to 28 countries (depending on the technologies) for the period 1984–2009, with variables measuring risk-mitigating innovations, disaster impacts and country characteristics. The data are taken from a variety of sources, described in greater detail below. As noted earlier, we consider three separate risk-mitigating technologies: flood control, drought-resistant crops and quake-proof buildings. The choice of technologies and disasters studied is influenced by the availability of both adequate data on disaster impacts and clearly identifiable technologies in the patent data.

Innovation and knowledge stocks

Our dependent variable is the flow of risk-mitigating innovations, which is measured by the number of successful patent applications filed by domestic residents in a country in a given year. All our patent data are taken from an online global patent database, *Delphion.com,* and are identified through either International Patent Code (IPC) or key word searches. A more detailed description of our patent search strategy is provided in online Appendix 1. Given the issue of cross-country patenting (i.e., inventors can patent the same innovation in multiple countries where they desire protection), we take a set of procedures in cleaning the data to ensure that (1) one patent represents one unique innovation and is counted only once in our sample; and (2) each patent is assigned to only one country where the first inventor indicated in the patent document is located.[16]

It is important to acknowledge that patents, while a common measure of invention used in the innovation literature, are not a perfect measurement (Griliches, 1990; Nagaoka et al, 2010). There are two major shortcomings of using patent data: first, the number of patent applications in a country is highly subject to its patent system. Thus, we control for country heterogeneity by including the overall number of patents in each country in our regression. Second, not all inventions get patented. Inventors have the right to hide or reveal their inventions. Because the propensity to patent varies by technology, we do separate regressions for each technology so our identification strategy focuses on patenting changes within a single technology.

We construct a country's stock of knowledge in a specific technology field using patent counts based on the perpetual inventory model, which assumes the knowledge stock depends on a distributed lag of the current and past flows of innovations:

$$K_{jit} = PAT_{jit} + (1-\rho)K_{jit-1} \tag{7}$$

ρ is the rate of stock depreciation, which we assume to be 15 percent following the conventional innovation literature. Using a depreciation rate implies the patent/knowledge produced earlier become less valueable and relevant for today's innovations. For the first year's knowledge stock, we simply equate the patent counts in the first year to knowledge stock because most countries have zero patents in their first year of our estimation period.[17] For ease of interpreting the effect of knowledge stock, we use the log of the value of knowledge stock plus 1 in our regressions.

[15] To address the endogenous regressor issue, we have also tried other approaches following the literature on panel count-data models. For example, Chamberlain (1992), Wooldridge (1997) and Windmeijer (2000) have suggested a quasi-differencing GMM estimator using the lagged x_{it} as instruments. This approach not only allows the unobserved heterogeneity to correlate with regressors but no longer rests on the strict exogeneity assumption. But the precision of the estimator may be hampered if the regressors are highly persistent over time, which thus have less relevance for the differenced terms. We have found the same problem when we applied this approach to our data.

[16] For example, a U.S. inventor can apply to patent his/her innovations at the U.S. Patent and Trademark Office as well as in other countries. Filings of the same invention in multiple countries are known as patent families. As our goal is to identify unique inventions, we only count each patent family once. For example, a patent filed by a US inventor in both the US and a foreign country counts as a single US invention. Likewise, if a foreigner chooses to file patent application only in the United States, we assign that patent to the country in which the inventor resides. Also note that nearly all patent applications are first filed in the home country of the inventor. Also note that for most patent applications involving multiple inventors, these inventors are from the same country. Patents with inventors from multiple countries are rare. For example, for flood control, we only find one patent with multiple inventors from different countries: one from Italy, and one from Germany.

[17] In most applications of perpetual inventory model, the starting stock is calculated by dividing the first year's flow by average annual logarithmic growth plus the depreciation rate (e.g., Coe and Helpman, 1995). This method cannot be applied in our case, because many countries in our sample have zero patents during the years studied. We feel safe to do so also because many countries have zero patents in their first year in our data set. Moreover, because most our regressions begin in 1984 but our patent data begin in 1974, we have ten years of historical data for most countries to construct the initial knowledge stock.

Disaster data

We measure disaster severity, our key independent variable, using both human fatalities and economic losses from the natural disasters, with data taken from two sources. We use drought and floods data from the Emergency Event Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disaster. Although this database is publically assessable and used in most cross-country disaster studies, the accuracy of its data has been questioned given its humanitarian focus and specific thresholds for events to be included.[18] Although we can identify no better alternative for information on flooding and droughts, we collect data on earthquakes from the National Geophysical Data Center's (NGDC) Significant Earthquake Database.[19] This database is preferred to EM-DAT because it contains richer information on earthquake physics (e.g., magnitude and Modified Mercalli Intensity), much longer timespan and more small-impact events that do not meet the EM-DAT threshold. All the monetary losses from disasters are adjusted at the 2005 level by the World Bank GDP deflator index.[20]

Instrumental variables

In addition to disaster impacts, we also collect data on the physical disaster intensity to instrument for the endogenous disaster and knowledge stock variables. The instrumental variables used in each disaster-technology regression are summarized in Table 1. Specifically, we instrument for the disaster variables using a corresponding distributed lag of disaster magnitude measures. Considering the potential influence of population's exposure on disaster outcomes, we also include a distributed lag of a country's population density, with the data taken from the World Bank Development Indicators. Given the availability of rich pre-sample data, we instrument for the lagged knowledge stock using the magnitude information over a much longer period from year $t-1$ through year $t-25$, with some variables already being included in the set of instruments for disaster impacts. The relevance of all the instrumental variables is presented in Appendix Table 5.

Both floods and droughts are related to an unusual amount of rainfall. Hence, we measure their physical magnitude using precipitation data from the Tyndall Center for Climate Change Research. This data set contains information on monthly, quarterly and annual mean precipitation weighted by area (in millimeters) and aggregated at the country level between 1901 and 2012. To capture weather extremes, we construct a "rainfall anomaly" measure by calculating the proportional deviation of annual precipitation from a country's long-run average annual precipitation over the period of 1901–2000.[21] Positive values indicate excessive rainfall, while negative values indicate rainfall deficiencies relative to normal levels.

We create additional variables to capture the physical intensity specific to these two disasters. For floods, considering that the rainfall anomaly variable does not fully account for the temporal variation of rainfall within a year, we use the same data set to create another variable measuring the number of months in which the amount of precipitation exceeds 150 percent of the long-term average monthly precipitation. Moreover, given the fact that many flooding events are induced by storms, we calculate the number of storms (including tropical storms, subtropical storms and extratropical storms) a country experienced in a given year, using storm data from the International Best Tract Archive for Climate Stewardship (IBTrACS) provided by the National Climate Data Center of the National Oceanic and Atmospheric Administration (NOAA). The IBTrACS data, which are compiled from numerous tropical cyclone datasets, provide the most complete global set of individual storm events and track its positions (latitude and longitude) at 6-hour intervals. We use geospatial software to map the storm data to affected countries and calculate the frequency of storm events within a country in a given year. For drought, given its chronic nature, we follow Felbermayr and Groschl (2013) and create a drought indicator (also using the precipitation data from Tyndall Center), which takes the value of 1 if a country's precipitation is below 50 percent of the long-run average monthly mean in at least three subsequent months or at least five months within a year (zero otherwise).

For earthquakes, we use the Richter scale, provided in the NGDC database, as a strength measure of seismic activities. One issue arising here is that the original database records individual earthquake events, which differs from the unit of observation in our panel. We thus collapse the events data to the country-year level and construct three variables to measure the physical intensity of earthquakes: a dummy variable indicating whether there is an earthquake in a country in a

[18] EM-DAT includes events with either more than ten fatalities, over 100 people affected, a declaration of a state of emergency, or a call for international assistance. Therefore, this database tends to underreport small disaster events, and in particular, those occurring in developed countries. The EM-DAT data are compiled from a variety of sources including the United Nations, governmental and non-governmental organizations, research institutes and the press. It contains information on disaster events from 1900.

[19] The NGDC database includes an earthquake event with either at least $1 million damage, more than ten fatalities, a magnitude 7.5 or greater or Modified Mercalli Intensity X or greater, or a tsunami. The earthquake data are compiled from multiple sources including the U.S. Geological Survey, EM-DAT, reconnaissance reports, regional and local earthquake catalogs, newspapers and journal articles.

[20] It is important to note that the monetary losses reported by EM-DAT and NGDC database reflect only the direct damages caused by disasters (e.g., destroyed and damaged properties or capital stocks). These figures do not include any indirect damages or welfare losses resulting from the initial destructions, such as the forgone GDP and loss of potential production.

[21] In other words, we normalize the annual precipitation by subtracting each country's long-run average and dividing by each country's long-run standard deviation.

Table 1
Summary of instrumental variables.

Technology	Instrumental variables
Flood control	$\sum_{n=0}^{25} anomaly_{it-n}$
	$\sum_{n=0}^{25} month_{it-n}$
	$\sum_{n=0}^{25} storm\_count_{it-n}$
	$\sum_{n=0}^{7} pop\_density_{it-n}$
Quake-proof building	$\sum_{n=0}^{25} quake\_indicator_{it-n}$
	$\sum_{n=0}^{25} max\_magnitude_{it-n}$
	$\sum_{n=0}^{25} quake\_counts_{it-n}$
	$\sum_{n=0}^{5} pop\_density_{it-n}$
Drought-resistant crop	$\sum_{n=0}^{25} anomaly_{it-n}$
	$\sum_{n=0}^{25} drought\_indicator_{it-n}$
	$\sum_{n=0}^{5} pop\_density_{it-n}$

Notes: *Anomaly* represents the rainfall anomaly variable (the proportional deviation of annual precipitation from a country's long-run average annual precipitation over the period of 1901–2000). *Month* measures the number of months in which the amount of precipitation exceeds 150 percent of the long-term average monthly precipitation. Storm_count measures the number of storms in a country-year. *Quake_indicator* is a dummy variable indicating whether there is an earthquake in a country-year. *Max_magnitude* is the maximum magnitude of all earthquakes in a country-year. *Quake_counts* measures the total number of earthquakes measuring six and above on the Richter scale in a country-year. *Drought_indicator* is a dummy variable taking the value of 1 if a country's precipitation is below 50 percent of the long-run average monthly mean in at least three subsequent months or at least five months within a year (zero otherwise). *Pop_density* represents the population density in a country year.

given year, the maximum magnitude of all earthquakes in a country in a given year, and the total number of earthquakes measuring six and above on the Richter scale in each country per year. [22]

Country characteristics

To measure a country's income, we use data on real GDP per capita from Penn World Table (7.0 version). We use the polity variable from the POLITY IV project, which takes a value from -10 to 10 to indicate the openness of a country's political institutions. Higher values suggest a more democratic and open political institution. As discussed above, countries are different in terms of their science bases, patent systems and general propensity to patent innovations. Thus, we use the total number of patent applications filed (within the country) by a country's residents to control for this country characteristic. The data come from the World Bank World Development Indicators and the database of the World Intellectual Property Organization.

Sample statistics

In this study, we pair each type of natural disasters with one risk-mitigating technology, and accordingly construct a sample with the selection criteria that a country should have at least five patents in a given technology field between 1974 and 2009. Therefore, our sample size varies according to different technology types. Appendix 2 lists the countries included for each technology. Meanwhile, it should be noted that although our patent data generally become available in 1974, we deliberately choose to start our estimation period at least ten years later to allow the stock to accumulate for ten years before it enters into the estimation equation.[23]

Table 2 provides national summary statistics reporting the average deaths and damages from natural disasters per year by disaster type, and total patent counts by technology type for the period 1970–2009. A large majority of our sample countries are industrialized countries. This is consistent with the notion that most of the global R&D activities are carried out by developed countries (National Science Board, 2010) because they have higher demand and more resources for science, technology and innovation. In particular, the United States, Germany and Japan appear to play leading roles in patenting on these mitigating technologies. Notably, China seems to be most severely impacted by all three types of disasters among all sample countries, while it also has a large number of patents on these technologies. To compare across disasters, while our samples for earthquakes and floods include the major affected countries, we leave out several countries

[22] Using the same database, we also collapse the earthquake events to country-year to obtain the human and economic losses. Note that we use the maximum magnitude because the earthquake impact is measured by the sum of deaths and damages in a country-year. We use scale six as a threshold here, given the conventional view that earthquakes below six usually cause minor damages. Also note that if a country experiences small earthquakes (below six), it can still be captured by the maximum magnitude variable.

[23] We choose 1974 as the beginning year in our selection timeframe because patent data for many countries first appears in the Delphion database in the mid-1970s. However, there is no patent documented for the flood-control technology worldwide until 1976. Thus, our estimation period for flooding begins 10 years later in 1986.

Table 2
Natural disaster and patent statistics for sample nations, 1970–2009.

Disaster/ ***Technology***	**Flood**		***Flood control***	**Earthquake**		***Quake-proof Building***	**Drought**		***Drought-resistant crop***
Country	Average deaths	Average damages	Total patent counts	Average deaths	Average damages	Total patent counts	Average deaths	Average damages	Total patent counts
Argentina	.	.	.	1.93	5.5	10	.	.	.
Australia	5.08	161.28	10	0.3	0.17	12	0	405.93	39
Austria	0.98	96.13	5	0.03	0	7	0	0	6
Belarus	.	.	.	0	0	7	.	.	.
Belgium	.	.	.	0.05	2.17	8	0	0	22
Brazil	.	.	.	.	.	.	0.5	214.86	5
Bulgaria	.	.	.	0.08	0.2	8	.	.	.
Canada	0.93	64.22	16	0	0	35	0	270.53	39
China	949.33	4140.81	305	9055.73	3347.25	291	88.35	685.72	636
Czech Republic	1.85	128	46	.	.	.	.	.	.
Denmark	.	.	.	0	0	6	.	.	.
France	4.75	157.69	34	0.23	0	134	0	57.78	46
Germany	1.08	375.95	227	0	9.28	149	0	0	182
Greece	.	.	.	6.78	107.88	31	.	.	.
Hungary	7.73	21.173	10	0	0	11	0	35.03	10
India	.	.	.	.	.	.	8	78.36	7
Israel	.	.	.	.	.	.	0	2.16	23
Italy	14.43	634.39	9	152.75	1520.69	42	0	0.0263	.
Japan	28.15	329.41	415	146.35	4211.9	9928	0	0	93
Mexico	.	.	.	266	175.51	10	0	47.71	5
Netherlands	0.03	18.07	8	0.03	3.26	11	0	0	18
Norway	.	.	.	.	.	.	0	0	.
New Zealand	.	.	.	0.08	8.1	29	0	3.13	12
Poland	2.35	146.64	22	0	0	13	.	.	.
Republic of Korea	57.1	91.14	187	0	0	217	0	0	48
Romania	16.7	105.69	7	39.98	82.73	23	.	.	.
Russia	13.58	68.5	59	100.93	753.5	85	0	0	20
Spain	.	.	.	0	1.27	25	0	396.07	8
Sweden	0.28	11.49	10	0	0	6	0	0	.
Switzerland	0.25	72.26	13	0	0	12	0	0	13
Ukraine	.	.	.	0	0	22	.	.	.
United Kingdom	1.23	415.47	89	0	0	33	0	0	15
United States	35.5	1356.08	91	5.68	1406.02	323	0	203.8	864
Total	1141.33	8394.393	1563	9775	11,629.93	11,478	96.85	2401.1063	2111

Notes: Deaths are in persons and economic damages are in million US dollars (2005 level). The average values refer to average deaths/damages per month. According to our sample selection criteria, countries with less than five patents in the given technology are not included in the sample and are thus indicated as "." in the table. For these excluded countries, we don't indicate their disaster impact information. But this by no means implies these countries have never been hit by any disasters.

that often experience severe droughts because many of them are poor countries with very few innovations.[24] This suggests countries that are most adversely affected possess limited capacity to innovate, which would further exacerbate their vulnerability to natural disasters.

Table 3, Panel A reports the descriptive statistics of main variables in the analysis. To provide a sense of scale of the natural disasters, Panel B shows the human and economic losses on an event basis and the most damaging events over our sample period, including the affected country and year of occurrence. In terms of average damages per country and year (shown in Panel A), earthquakes and floods appear to have caused much larger losses on our sample countries than droughts. This is consistent with the statistics in Yang (2008a) that floods and earthquakes altogether accounted for about 60 percent of the total global damages from natural disasters for 1970–2002, which is ten times the drought damages. However, Panel B shows that droughts occur in our sample countries less frequently than the other two types of disasters. As noted earlier, this is partially because the countries that are often hit by droughts are not patenting and thus not included in our sample. Such results also demonstrate the importance of considering the endogeneity of damages, as one reason higher income countries report fewer drought events is that they are better equipped to deal with drought, such as through

[24] The statistics of global drought impacts by country (based on the EM-DAT data) reveals that of the top 15 countries most often hit by drought from 1970 to 2010, only five (China, Brazil, Australia, India, the United States) are included in our sample. The other countries are Mozambique, Ethiopia, Kenya, Bolivia, Somalia, Honduras, Indonesia, Mauritania, Philippines and Sudan.

Table 3A
Descriptive statistics.

Technology	*Flood control*		*Quake-proof building*		*Drought-resistant crop*	
Dependent variable	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Patent counts	3.28	6.73	15.49	74.41	4.24	14.23
Independent variables						
Deaths (thousand)	0.07	0.42	0.14	3.05		
Foreign deaths (thousand)	0.71	1.65	2.06	9.05		
Damages (2005 US$, billion)	0.57	2.53	0.51	7.19	0.006	0.098
Foreign damages (2005 US$, billion)	4.17	6.19	2.91	12.1	0.69	2
Log domestic knowledge stock	1.6	1.39	1.96	1.57	1.32	1.38
Real GDP per capita (2005 US$, thousand)	23.99	10.77	21.59	10.88	22.43	11.08
Institution index (− 10 to 10)	8.03	4.59	7.55	4.98	8.03	4.36
Total patent applications (thousand)	38.66	83.02	26.08	69.53	33.3	78.03
Instrumental variables						
Maximum earthquake magnitude			1.44	2.74		
Count of earthquakes (≥ 6)			0.3	0.89		
Quake indicator (dummy)			0.22	0.42		
Drought indicator (dummy)					0.02	0.15
Number of flooding months	1.13	1.19				
Precipitation anomaly	0.17	1.01			0.16	1.02
Count of storms	1.65	3.05				
Population density (people per square kilometer)	157.75	137.5	134.27	128.2	167.03	148.58
Number of countries	19		28		21	
Sample time span	1986–2009		1984–2009		1984–2009	

Notes: The statistics on disaster variables are calculated taking into account the length of the distributed lags included in the regressions. They are therefore based on the period 1979–2009.

better irrigation practices. Thus, while droughts are reported less frequently in our sample countries, when a drought is reported, the average damage caused per event is highest among the three disaster types.

Results

Impacts from domestic disaster shocks

Table 4 presents the estimation results of our main specification using either deaths or monetary losses as the measure of disaster impacts. Because we use the Poisson model for estimation, we are able to interpret the coefficients of disaster losses in a semi-elasticity form and of other variables in logs (e.g., knowledge stock and income) as elasticities. Two things are important to note here: first, for droughts we focus on only economic damages because a majority of our sample countries have zero deaths over the estimation period, which makes it difficult to identify the effect of disaster fatalities on innovations. Second, based on our sensitivity tests (Appendices 3 and 4), we use a five-year distributed lag for earthquakes and droughts, while extending the lag structure to seven years in the case of floods.[25]

The results show the impacts of recent disasters generally have a significant, stimulating effect on domestic patenting activities for all technologies concerned. The long-term cumulative effect, which is a linear combination of all the disaster variables' coefficients above, is statistically significant and positive across all technologies. Such evidence supports our principal hypothesis that natural disasters lead to risk-mitigating innovations and the amount of patent applications increases with the severity of these shocks.

In particular, floods have an exceptionally long-term stimulating effect on flood-control innovations. At the same time, the magnitude of impacts generally declines with the passage of time, suggesting innovation is most responsive to the most recent events. The coefficients on the current-year flood impact indicate that an additional 1000 deaths leads to a 57 percent increase in patent applications, and one billion dollars of monetary damages result in an 8.14 percent increase in patent applications filed in the same year. The cumulative long-run effect of 1000 deaths caused by flooding increases flood-control patent applications in the next seven years (including year t) by a factor of three, whereas one billion of damage increases cumulative patenting by 30 percent, with innovation mostly concentrated in the current year and the past three. While the magnitude of the effect of deaths is larger, it is important to note that monetary damages, rather than large death counts, are the primary result of flooding in the countries in our sample. To put these numbers in perspective, the 2008 Midwest flood

[25] We find the coefficients on lagged disaster variables generally become insignificant beyond five years for earthquakes and droughts, while they become insignificant beyond seven years for floods.

Table 3B
Statistics on disaster events.

Disaster	Floods	Earthquakes	Droughts
Frequency in sample countries	672	493	55
Mean deaths per event	63.61	238.26	
Mean monetary loss per event (2005 b US$)	0.486	0.874	0.966
Max. deaths	6303	87,724	
	China-1980	China-2008 (*Wenchuan Earthquake*)	
Max. monetary loss (2005 US$, billion)	37.09	161.13	17.21
	China-1998	Japan-1995 (*Kobe Earthquake*)	China-1994

Notes: The flood and drought data are taken from EM-DAT disaster list. The earthquake data come from the NGDC Significant Earthquake Database. It should be noted that EM-DAT provides disaster data in both country-year panel and event formats. The statistics on disaster variables are calculated taking into account the length of the distributed lags included in the regressions. They are therefore based on the period 1979–2009.

in the United States, which resulted in around $9 billion monetary damages (above the 95th percentile for all flooding events in our sample), would increase flood control patent applications in the next seven years by 270 percent.

For earthquakes, we find that the effects of earthquakes on quake-proof building innovations are mainly spread across a six-year horizon. An additional 1000 deaths increase the number of patent applications filed in the current year and following five years by 18.2 percent, and $1 billion economic losses from earthquakes increases the number of patent applications filed in the current year and following five years by 2.8 percent. For more concrete examples, the most expensive earthquake so far, Kobe Earthquake (Japan, 1995), incurred more than $160 billion losses, which would increase the quake-proof building patent applications in the following years by a factor of 4.5. A more moderate earthquake, such as the 1994 Northridge Earthquake that resulted in $50 billion in damages, would increase the patent applications in the following years by 140 percent.

Finally, for the drought-resistant crop technology, the effect of droughts on patenting is also positive and statistically significant in most lagged years. The cumulative effect of drought damages is the largest of our three disasters. Not only is the magnitude of the cumulative effects larger, with an additional $1 billion drought damages increasing long-run patent applications by nearly 40 percent, but the mean losses per event are larger for droughts, as shown in Table 3B. To put these results in the context, a severe drought such as the US drought of 2002, which resulted in $3.6 billion losses nationwide (around the 95th percentile for all drought events in our sample), would increase drought-resistant crop patent applications in 2002–2007 by 139 percent.

As we discussed earlier, the knowledge stock can affect risk-mitigating innovations through multiple channels, thereby making its final effect somewhat ambiguous. From Table 4 we see the coefficients of one-year lagged knowledge stock variables are consistently significant and positive in the earthquake case: one percent increase in last year's knowledge stock leads to a 0.8–0.9 percent increase in today's patent applications. This suggests that the earlier knowledge stock serves as a building block for future innovations even after considering its possible competing effects on risk-mitigation innovations as part of a country's existing adaptive capacity. By contrast, the effects of the knowledge stock on the patenting activity for flood-control and drought-resistant crop technology are smaller and insignificant, suggesting the competing forces of knowledge as a building block and knowledge representing increased adaptive capacity at work. Likewise, income and institutional quality, as the components of a country's adaptive capacity, also have a mixed effect on risk-mitigating innovations. One possible reason is that the institutional variable exhibits little variation within countries over time for most of our sample countries. Therefore, it is not surprising to see few statistically significant results for these variables after controlling for the country fixed effects.

Impact of foreign disasters

Given that globalization renders countries increasingly interdependent with each other, a salient disaster shock may generate a global effect by increasing risk perception in other countries. One anecdotal example is that the Netherlands launched a full re-assessment of its risk management policy soon after Hurricane Katrina hit Louisiana in 2005. The possibility of such a "contagious effect" has also received support in micro-level studies, as some researchers find that the indirect experiences, which people obtain from others' experiences, can also influence the risk perception of those not directly affected by a disaster and induce their precautionary behaviors (e.g., Tyler, 1984). A recent study (Hallstrom and Smith, 2005) of the 1992 Hurricane Andrew shows that homeowners in an unaffected county also responded to this disaster event, leading to a 19 percent decline in local property values.[26] Nevertheless, the extent of the influence of indirect experiences usually depends on the context, and plays a much less important role in affecting risk perception compared to direct personal experiences (Hertwig et al. 2004; Viscusi and Zeckhauser, 2014). However, most of these studies look at the individual and community levels. Given the greater heterogeneity across countries in their political, socio-economic, and cultural characteristics, whether innovators also respond to foreign disasters in a cross-national setting remains to be addressed.

[26] This study focuses on Lee County, which did not experience damages from Hurricane Andrew but also face a high risk of flooding and storm damages. While Hurricane Andrew was a "near-miss" for the county, the authors show that this shock conveys risk information to change the behavior of homeowners in the county.

Table 4
Innovation in response to domestic shocks.

Technology	*Flood control*		*Quake-proof building*		*Drought-resistant crop*
Impact measure	**Death**	**Damage**	**Death**	**Damage**	**Damage**
Year t	0.570*** (0.132)	0.0814*** (0.0234)	0.0116*** (0.00275)	0.0140*** (0.00172)	0.0954* (0.0559)
Year $t-1$	0.425*** (0.0693)	0.0465** (0.0206)	−0.00627 (0.00447)	0.00264 (0.00208)	0.0201 (0.0437)
Year $t-2$	0.565*** (0.157)	0.0550** (0.0239)	0.0626** (0.0294)	0.00290* (0.00158)	0.0996** (0.0492)
Year $t-3$	0.497** (0.223)	0.0467* (0.0270)	0.0190 (0.0296)	0.00175* (0.000931)	0.122* (0.0738)
Year $t-4$	0.185 (0.116)	0.0329 (0.0233)	0.0303 (0.0374)	0.00274** (0.00131)	0.0680** (0.0335)
Year $t-5$	0.175*** (0.0582)	0.0158 (0.0106)	0.0644** (0.0293)	0.00367*** (0.00111)	−0.0192 (0.0393)
Year $t-6$	0.370*** (0.138)	0.0312** (0.0146)			
Year $t-7$	0.188*** (0.0521)	−0.00314 (0.0110)			
Cumulative effect	2.975*** (0.7682)	0.306** (0.1476)	0.182** (0.0896)	0.028*** (0.0049)	0.385*** (0.1259)
Log knowledge stocks (year $t-1$)	0.122 (0.249)	0.0315 (0.347)	0.914*** (0.188)	0.796*** (0.229)	0.135 (0.466)
Log GDP per capita	2.816 (1.913)	1.471 (1.743)	0.803 (0.879)	−0.375 (0.590)	1.999* (1.209)
Institution index	0.515 (0.567)	0.876 (0.877)	0.258* (0.145)	0.365 (0.241)	0.680 (1.515)
Log patent applications	1.198 (0.911)	1.109 (0.955)	0.402* (0.218)	0.498** (0.204)	−0.557 (0.534)
Observations	443	443	699	699	490
GMM criterion	0.1762	0.2148	0.1550	0.1555	0.0261
Number of countries	19	19	28	28	21
Timespan	1986–2009		1984–2009		1984–2009

Notes: Deaths are measured by 1000 people and economic damages are in \$1 billion at 2005 price. All the models include country and year fixed effects. Standard errors are in parentheses, adjusted for clustering at the country level.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

While our model already controls for foreign disasters indirectly through year fixed effects, in this section we further explore the influence of foreign disasters by asking whether natural disasters occurring in nearby foreign countries are more likely than other foreign events to induce domestic risk-mitigating innovations. Nearby disasters are of interest for two reasons. First, geographic proximity leads countries to share similar environmental characteristics and similar risk profiles. Second, as flows of knowledge tend to dampen with increased distance (see, e.g. Verdolini and Galeotti, 2011), geographic proximity makes it more likely that nearby foreign countries represent a potential market for new innovations. To explore the effect of nearby disasters, we group countries by continent and create variables measuring foreign disaster impacts occurring in other countries on the same continent as country i.[27] As with domestic disasters, we include a distributed lag of the continent-based foreign disaster variables, measured by either human or economic losses, into Eq. (6) while using the same sets of instrumental variables to instrument for domestic disaster impacts as well as the domestic knowledge stock. As our model already controls for the global effect of foreign disasters via year fixed effects, the continent-specific variables test whether nearby disasters are more likely to spur innovation than other foreign disasters.

Table 5 presents the estimation results. First note that the coefficients on both domestic disaster impacts and our control variables are largely similar to the results of the model only using domestic impacts (Table 4). The only exception is in the earthquake case the cumulative effect of domestic deaths on quake-proof building innovations over the recent five years is no longer statistically significant. In terms of foreign shocks, we only find a differential effect for foreign disasters occurring

[27] That is, foreign deaths and foreign damages on the same continent equal the sum of total deaths/damages by continent (including both sample countries and non-sample countries) in a given year minus domestic deaths/damages in country i.

Table 5
Innovation in response to domestic and foreign shocks.

Technology	***Flood control***		***Quake-proof Building***		***Drought-resistant crop***
Impact measure	**Death**	**Damage**	**Death**	**Damage**	**Damage**
Domestic shocks					
year t	0.504***	0.0705***	0.0188**	0.00694***	0.130**
	(0.151)	(0.0181)	(0.00859)	(0.00170)	(0.0660)
Year $t-1$	0.344***	0.0647***	−0.00239	0.00388**	0.0276
	(0.121)	(0.0147)	(0.00758)	(0.00162)	(0.0496)
Year $t-2$	0.503***	0.0711***	0.0548*	0.00121	0.107**
	(0.0687)	(0.0197)	(0.0310)	(0.00105)	(0.0504)
Year $t-3$	0.363**	0.0396*	0.0382	0.000891	0.138**
	(0.158)	(0.0204)	(0.0450)	(0.00135)	(0.0651)
Year $t-4$	−0.0129	0.0289	−0.00682	0.000469	0.0671**
	(0.0818)	(0.0209)	(0.0417)	(0.00122)	(0.0298)
Year $t-5$	0.0794	0.0229*	0.0356	−0.000262	0.00694
	(0.0736)	(0.0118)	(0.0324)	(0.00104)	(0.0244)
Year $t-6$	0.423***	0.0321***			
	(0.119)	(0.0106)			
Year $t-7$	0.169**	−0.00575			
	(0.0708)	(0.0104)			
Cumulative effect	2.372***	0.324***	0.138	0.013***	0.477***
	(0.5640)	(0.1091)	(0.0902)	(0.0043)	(0.1542)
Foreign shocks					
Year t	0.0450	0.00568	0.00742	−0.00212*	−0.142
	(0.0578)	(0.00575)	(0.00741)	(0.00111)	(0.111)
Year $t-1$	0.0980**	0.0264***	0.00402	0.00693***	−0.0540
	(0.0486)	(0.00639)	(0.00481)	(0.00199)	(0.0924)
Year $t-2$	0.171***	0.0183***	−0.00285	−0.00412	−0.0701
	(0.0501)	(0.00634)	(0.00354)	(0.00652)	(0.0930)
Year $t-3$	−0.0106	0.000237	−0.00371	−0.00474	0.105**
	(0.0798)	(0.00365)	(0.00448)	(0.00837)	(0.0490)
Year $t-4$	−0.108*	0.000640	−0.00453	−0.00382	−0.00167
	(0.0589)	(0.00502)	(0.00456)	(0.00322)	(0.0363)
Year $t-5$	0.0108	0.000496	−0.00907***	−0.00763***	0.0279
	(0.0332)	(0.00455)	(0.00166)	(0.00245)	(0.0255)
Year $t-6$	0.106**	0.00280			
	(0.0445)	(0.00393)			
Year $t-7$	−0.0678*	−0.0108*			
	(0.0386)	(0.00576)			
Cumulative effect	0.7977***	0.0438***	−0.0087	−0.0155	−0.1341
	(0.1940)	(0.0121)	(0.0079)	(0.0203)	(0.2931)
Log knowledge stocks (year $t-1$)	0.138	0.0800	0.885***	0.822***	−0.204
	(0.221)	(0.201)	(0.190)	(0.147)	(0.392)
Log GDP per capita	1.412	1.336	1.265	0.699	1.788
	(1.795)	(1.711)	(0.954)	(0.753)	(1.100)
Institution index	0.922	0.849	0.301	0.108	1.327
	(0.836)	(0.636)	(0.203)	(0.139)	(2.091)
Log patent applications	1.143	1.128*	0.318	0.402	−0.513
	(0.802)	(0.640)	(0.290)	(0.346)	(0.450)
Observations	443	443	699	699	490
GMM criterion	0.2147	0.2468	0.1754	0.1726	0.0221
Number of countries	19	19	28	28	21
Timespan	1986–2009		1984–2009		1984–2009

Notes: Deaths are measured by 1000 people and economic damages are in $1 billion at 2005 price. All the models include country and year fixed effects. Standard errors are in parentheses, adjusted for clustering at the country level.

*** $p<0.01$.

** $p<0.05$.

* $p<0.1$.

on the same continent in the case of flooding. For example, 1000 deaths from regional foreign floods one year and two years ago would increase the domestic flood-control patent applications by 9.8 percent and 17.1 percent, respectively. We find similar results using economic damage as a disaster measure. For both deaths and damages, the cumulative long-term effect of foreign floods over the eight-year horizon (from year t through year $t-7$) is statistically significant, but the magnitude is much smaller than the effect of domestic influence on innovations. This finding is not surprising, and suggests that domestic disasters matter more than foreign shocks in shaping innovation responses.

By contrast, we find little evidence of a differential effect for foreign disasters on the same continent for earthquakes and droughts. The cumulative effect is statistically insignificant in both cases, with only a couple of individual years having significant positive effects on innovation. However, as our model also controls for the global effect of disasters shocks through year fixed effects, one cannot conclude that foreign shocks do not matter at all. For instance, given the presence of the global crop market and the concentration of R&D by a few biotech multinational corporations, the innovation response to droughts might not be confined to a certain geographic region. Similarly, a big earthquake in California may raise concerns for the residents in Japan and impel the Japanese engineers to improve their building safety. However, the same earthquake might not alter the risk perception of the neighboring Canadians much, given their relative lower risk of earthquakes. We leave studying the effect of global markets and different risk profiles across countries for future research.

Conclusion

Natural disasters cause tremendous human causalities and significant economic losses worldwide. But apart from this, what do people learn from suffering natural disasters? Are they constantly adapting or only reacting after being hit by a disaster shock? These are important questions for both researchers and policy makers to consider, particularly given the increased threats of climate change. Until now, there has been no systematic study of innovation as an adaptation response to climate change. This paper fills this gap, linking three types of natural disasters (floods, droughts and earthquakes) to a set of mitigation technologies.

By introducing the idea of "risk-mitigating innovation," we conceptualize innovation as an important form of adaptation and develop a conceptual framework for assessing the effects of natural disasters on risk-mitigating innovations. Our empirical analysis, using a panel of up to 28 countries covering a period of 25 years, reveals a consistent stimulating effect of natural disasters on patents of risk-mitigating technologies. For all technologies included in this study, we provide strong evidence that risk-mitigating innovation in a country increases with the severity of its recent natural disasters. This finding suggests people are learning and adapting, but not until disasters have already occurred and losses have been incurred. This finding has important implications for both policymakers and modelers of climate policy because it suggests innovations that facilitate adaptation to climate change are unlikely to come from the private sector until after climate damages have been experienced. The potential role of public R&D support to facilitate earlier improvements in risk-mitigating technologies thus deserves investigation in future research. Our empirical evidence of reactive adaptation may also suggest people are less likely to adapt to those gradual changes (e.g., sea level rise and temperature rise) than the extreme events related to climate change because it takes much longer for the former to be felt and effect a change in risk perception.

Moreover, our study shows that in the case of flooding innovators not only respond to domestic shocks but also respond to natural disasters occurring in nearby countries, although the influence of foreign shocks is much smaller than domestic ones. It is also important to acknowledge that in this study, we construct the measure of foreign disaster shocks in a relatively coarse way. In fact, not all natural disasters that have occurred abroad or in neighboring countries are relevant for domestic innovators. More analyses could be done in this regard; for example, taking into account the spatial geographic distance between countries or their similarities of baseline hazard.

Finally and most importantly, one distinction between this study and most other research on the economic impacts of natural disasters is that we focus on the behavioral change that may affect future disaster outcomes. In essence, innovation is a social learning and knowledge-generating process. Linking innovation and adaptation is particularly meaningful because this expands the conventional view on the highly localized nature of adaptation: innovation produces new knowledge and technologies that can potentially serve as a public good by being transferred to and adopted by non-inventors. Therefore, risk-mitigating innovations have the potential to reduce global disaster impacts in the face of climate change. In this context, more research is needed to explore the role of technological innovations in lessening disaster damages and facilitating climate adaptation. If these innovations are found to facilitate reduction in disaster risks effectively, it suggests policy makers should encourage more investment in developing and deploying new risk-mitigating technologies. This will also have important implications in the international context because the transfer and diffusion of these technologies may benefit developing countries, especially those vulnerable to natural hazards but lacking the technological capacity to adapt. The potential role of knowledge spillovers in international adaptation activities deserves more attention and investigation.

Acknowledgments

This work was supported by DOE Grant #DE-SC0005171. We thank two anonymous referees, Stephane Hallegatte, and seminar participants at Carnegie Mellon and the Oslo Centre for Research on Environmentally Friendly Energy for helpful comments on earlier versions of this paper.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jeem.2014.06.003.

References

Allison, P.D., Waterman, R.P., 2002. Fixed-effects negative binomial regression models. Sociol. Methodol. 32, 247–265.
Anbarci, N., Escaleras, M., Register, C.A., 2005. Earthquake fatalities: the interaction of nature and political economy. J. Public Econ. 89, 1907–1933.
Baez, J., de la Fuente, A., Santos, I., 2010. Do natural disasters affect human capital? An assessment based on existing empirical evidence. IZA Discussion Paper No. 5164.
Benson, C., Clay, E.J., 2004. Understanding the economic and financial impacts of natural disastersDisaster Risk Management Series, No. 4World Bank, Washington, DC.
Bosello, F., Carraro, C., De Cian, E., 2009. An Analysis of Adaptation as a Response to Climate Change. Copenhagen Consensus Center, Copenhagen Business School.
Boustan, L.P., Kahn, M.E., Rhode, P., 2012. Moving to higher ground: migration response to natural disasters in the early twentieth century. Am. Econ. Rev. Pap. Proc. 102 (3), 238–244.
Brooks, N., Adger, W., Kelly, P., 2005. The determinants of vulnerability and adaptive capacity at the national level and the implications for adaption. Glob. Environ. Change 15, 151–163.
Callen, M., 2011. Catastrophes and Time Preference: Evidence from the Indian Ocean Earthquake. Working Paper.
Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press, Cambridge.
Cameron, L., Shah, M., 2013. Risk-taking Behavior in the Wake of Natural Disasters. NBER Working Paper No. 19534.
Cassar, A., Healy, A., von Kessler, C., 2011. Trust, Risk and Time Preference after a Natural Disaster; Experimental Evidence from Thailand. University of San Francisco Working Paper.
Cavallo, E., Noy, I., 2010. The Economics of Natural Disasters. A Survey. Inter-American Development Bank. Working Paper series No. IDB-WP-124.
Chamberlain, G., 1992. Comment: Sequential Moment Restrictions in Panel Data. J. Business Econ. Stat. 10, 20–26.
Chhetri, N., Easterling, W.E., 2010. Adapting to climate change: retrospective analysis of climate technology interaction in rice based farming systems of Nepal. Ann. Assoc. Am. Geographers 100 (5), 1–20.
Coe, D.T., Helpman, E., 1995. International R&D spillovers. Eur. Econ. Rev. 39, 859–887.
Cuaresma, J.C., Hlouskova, J., Obersteiner, M., 2008. Natural disasters as creative destruction? Evidence from developing countries. Econ. Inq. 46, 2.
Cutter, S.L., Boruff, B.J., Shirley, W.L., 2003. Social vulnerability to environmental hazards. Social Sci. Q. 84, 242–261.
de Bruin, K.C., Dellink, R.B., Tol, R.S.J., 2009. AD-DICE: an implementation of adaptation in the DICE model. Clim. Change 95, 63–81.
Escaleras, M., Anbarci, N., Register, C., 2006. Public Sector Corruption and Natural Disasters: A Potentially Dead Interaction. No. 6005, Working Papers from Department of Economics, College of Business, Florida Atlantic University.
Easterling, W.E., 1996. Adapting North American agriculture to climate change in review. Agric. For. Meteorol. 80, 1–53.
Fankhauser, S., Smith, J.B., Tol, R.S.J., 1999. Weathering climate change: some simple rules to guide adaptation decisions. Eco. Econ. 30, 67–78.
Felbermayr, G., Groschl, J., 2013. Naturally Negative: The Growth Effects of Natural Disasters. CESIFO Working Paper No. 4439.
Ferreira, S., Hamilton, K., Vincen, J.R., 2013. Does development reduce fatalities from natural disasters? New evidence for floods. Environ. Dev. Econ. 18 (06), 649–679.
Finlay, J.E., 2009. Fertility Response to Natural Disasters: The Case of Three High Mortality Earthquake. World Bank Policy Research Working Paper 4883.
Griliches, Z., 1990. Patent statistics as economic indicators: A survey. J. Econ. Lit. 28 (4), 1661–1707.
Grothmann, T., Patt, A., 2005. Adaptive capacity and human cognition: the process of individual adaptation to climate change. Glob. Environ. Change 15, 199–213.
Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. Econometrica 50, 1029–1054.
Hallstrom, D., Smith, V.K., 2005. Market responses to hurricanes. J. Environ. Econ. Manage. 50 (3), 541–561.
Hicks, J.R., 1932. The Theory of Wages. Macmillan, London.
Intergovernmental Panel on Climate Change (IPCC) TAR, 2001. Climate Change 2001: Impacts, Adaptation and Vulnerability. IPCC, Third Assessment Report. Cambridge University Press.
Intergovernmental Panel on Climate Change (IPCC), 2012. Managing the risks of extreme events and disasters to advance climate change adaptation. In: Field, C.B., Barros, V., Stocker, T.F., Qin, D., Dokken, D.J., Ebi, K.L., Mastrandrea, M.D., Mach, K.J., Plattner, G.-K., Allen, S.K., Tignor, M., Midgley, P.M. (Eds.), A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK; New York, NY, USA.
Johnstone, N., Hascic, I., Popp, D., 2010. Renewable energy policies and technological innovation: evidence based on patent counts. Environ. Resour. Econ. 45 (1), 133–155.
Kahn, M., 2005. The death toll from natural disasters: the role of income, geography, and institutions. Rev. Econ. Stat. 87 (2), 271–284.
Kellenberg, D.K., Mobarak, A.M., 2008. Does rising income increase or decrease damage risk from natural disasters? J. Urban Econ. 63 (3), 788–802.
Kellenberg, D.K., Mobarak, A.M., 2011. The economics of natural disasters. Annu. Rev. Resour. Econ. 3, 297–312.
Keefer, P., Neumayer, E., Plumper, T., 2011. Earthquake propensity and the politics of mortality prevention. World Dev. 39 (9), 1530–1541.
Koppel, B.M., 1995. Induced innovation theory, agricultural research, and Asia's green revolution: a reappraisal. In: Koppel, B.M. (Ed.), Induced Innovation Theory and International Agricultural Development: A Reassessment, The John Hopkins University Press, pp. 56–72.
Kousky, C., 2012. Informing climate adaptation: A review of the economic costs of natural disasters, their determinants, and risk reduction options. Resources for the Future Discussion Paper, RFF DP 12-28.
Hallegatte, S., 2012. An Exploration of the Link Between Development, Economic Growth and Natural Risk. Policy Research Working Paper 6216. The World Bank.
Hertwig, R., Barron, G., Weber, E.U., Erev, I., 2004. Decisions from experience and the effect of rare events in risky choice. Psychol. Sci. 15 (8), 534–539.
Martin, W.E., Martin, I.M., Kent, B., 2009. The role of risk perception in the risk mitigation process: the case of wildfire in high risk communities. J. Environ. Manage. 91, 489–498.
Mulilis, J.P., Lippa, R., 1990. Behavioral change in earthquake preparedness due to negative threat appeals: a test of protection motivation theory. J. Appl. Soc. Psychol. 20, 619–638.
Nagaoka, S., Motohashi, K., Goto, A., 2010. Patent Statistics as an Innovation Indicator, Handbook of the Economics of Innovation Volume 2, 1083-1128Academic Press/Elsevier, Amsterdam, The Netherlands.
National Science Board, 2010. Science and Engineering Indicators 2010National Science Foundation, Arlington, VA.
Newell, R.G., Jaffe, A.B., Stavins, R.N., 1999. The induced innovation hypothesis and energy-saving technological change. Q. J. Econ. 114 (3), 941–975.
Paulo, G., 2008. The fixed effects negative binomial model revisited. Econ. Lett. 99 (1), 63–66.
Paxson, C., Rouse, C.E., 2008. Returning to New Orleans after Hurricane Katrina. Am. Econ. Rev. Pap. Proc. 98 (2), 38–42.

Perry, R.W., Lindell, M.K., 1986. Twentieth Century Volcanicity at Mt. St. Helens: The Routinization of Life Near an Active Volcano. Final Report of National Science Foundation Grant CEE-8322868.. Arizona State University, School of Public Affairs, Tempe.
Popp, D., 2002. Induced innovation and energy prices. Am. Econ. Rev. 92 (1), 160–180.
Popp, D., Newell, R., Jaffe, A., 2010. Energy, the environment and technological change. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, vol. 2. , Academic Press/Elsevier, Amsterdam, The Netherlands, pp. 873–937.
Rashky, P., 2008. Institutions and the losses from natural disasters. Nat. Hazards Earth Syst. Sci. 8, 627–634.
Rodima-Taylor, D., Olwig, M.F., Chhetri, N., 2011. Adaptation as innovation, innovation as adaptation: an institutional approach to climate change. Appl. Geography, 1–5.
Rogers, R.W., 1983. Cognitive and physiological processes in fear appeals and attitude change: a revised theory of protection motivation. In: Cacioppo, B.L., Petty, L.L. (Eds.), Social Psychophysiology: A Sourcebook, Guilford, London, UK, pp. 153–176.
Rogers, R.W., Prentice-Dunn, S., 1997. Protection motivation theory. In: Gochman, D.S. (Ed.), Handbook of Health Behavior Research. I: Personal and Social Determinants, Plenum Press, New York, NY, pp. 113–132.
Schumacher, I., Strobl, E., 2011. Economic development and losses due to natural disasters: the role of hazard exposure. Ecol. Econ. 72, 97–105.
Skidmore, M., Yoya, H., 2002. Do natural disasters promote long-run growth? Econ. Inquiry. 40 (4), 664–687.
Stefanovic, I.L., 2003. The contribution of philosophy to hazards assessment and decision making. Nat. Hazards 28, 229–247.
Smit, B., Wandel, J., 2006. Adaptation, adaptive capacity and vulnerability. Glob. Environ. Change 16, 282–292.
Smith, J.B., Vogel, J.M., Cromwell III, J.E., 2009. An architecture for government action on an adaptation to climate change. An editorial comment. Climate Change 95 (1–2), 53–61.
Smithers, J., Blay-Palmer, A., 2001. Technology innovation as a strategy for climate adaptation in agriculture. Appl. Geography 21, 175–197.
Tol, R.S.J., 2007. The double trade-off between adaptation and mitigation for sea level rise: an application of FUND. Mitig. Adapt. Strategies Glob. Change 12, 741–753.
Toya, H., Skidmore, M., 2007. Economic development and the impact of natural disasters. Econ. Lett. 94, 20–25.
Tyler, T.R., 1984. Assessing the risk of crime victimization: the integration of personal victimization experience and socially transmitted information. J. Soc. Issue 40 (1), 27–38.
United Nations Framework Convention on Climate Change , 2006. Technologies for Adaptation to Climate Change. 〈http://unfccc.int/resource/docs/publications/tech_for_adaptation_06.pdf〉.
United Nations International Strategy for Disaster Reduction, 2009. Reducing Disaster Risks through Science: Issue and Actions, the Full Report of the ISDR Scientific and Technical Committee 2009. 〈http://www.unisdr.org/files/11543_STCReportlibrary.pdf〉.
Verdolini, E., Galeotti, M., 2011. At home and abroad: an empirical analysis of innovation and diffusion in energy technologies. J. Environ. Econ. Manage. 61, 119–134.
Viscusi, W.k., Zeckhauser, R.J., 2014. The Relative Weights of Direct and Indirect Experiences in the Formation of Environmental Risk Beliefs. Vanderbilt University Law School Law and Economics Working Paper No. 14-6.
Weinstein, N.D., 1989. Effects of personal experience on self-protective behavior. Psychol. Bull. 103 (1), 31–50.
Windmeijer, F., 2000. Moment conditions for fixed effects count data models with endogenous regressors. Econo. Lett. 68, 21–24.
Wooldridge, J.M., 1997. Multiplicative panel data models without the strict exogeneity assumption. Econometric Theory 13, 667–678.
Yang, D., 2008a. Coping with disaster: The impact of hurricanes on international financial flow, 1970–2002. B.E. J. Econ.Anal. Policy 8 (1). (Advances), Article 13).
Yang, D., 2008b. Risk, migration, and rural financial markets: evidence from earthquakes in El Salvador. Soc. Res. 75 (3), 955–992.
Yohe, G., Tol, R., 2002. Indicators for social and economic coping capacity-moving toward a working definition of adaptive capacity. Glob. Environ. Change 12, 25–40.