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# NECESSITY AS THE MOTHER OF INVENTION: INNOVATIVE RESPONSES TO NATURAL DISASTERS

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## 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 including earthquakes, droughts and flooding on the innovation of their respective mitigation technologies. Using patent and disaster data, our study is the first to relate natural disasters to technology innovation, and also presents the first attempt to empirically examine adaptation responses to climate change across multiple sectors at the country level. 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.

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## 1. Introduction

How people cope with natural disasters is a question that has for long concerned both policy makers and researchers. This issue is gaining renewed attention nowadays, given the increasingly evident threats of climate change. Many climate scientists warn that global warming will likely increase the frequency and intensity of extreme weather events, thereby substantially raising the risk of disasters such as droughts, heat waves, floods and tropical cyclones (e.g., Van Aals, 2006). A recent report released by the Intergovernmental Panel on Climate Change (IPCC, 2012) confirms the link between climate change and natural disasters.[1] Moreover, it calls for policy makers to integrate disaster risks reduction into their efforts of climate change adaptation.

In this paper, we ask whether natural disasters lead to innovations of risk-mitigation technologies. Such technologies are analogous to those that may aid adaptation to climate change. A term initially used to explain biological evolution, adaptation is now more often applied 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 TAR, 2001: 72). In a broad sense, adaption takes form of various actions and measures, which often depend on the characteristics of local environment, particularly the natural hazards associated with climate change. Adaptation can be either proactive or reactive (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 the actions taken only after the disaster events happened.

[1] The report explicitly concludes "(A) changing climate leads to change in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events, and can result in unprecedented extreme weather and climate events" (IPCC 2012: 7). The report also highlights the impacts of those climatic or weather-related disasters: they have resulted in increased economic losses worldwide since 1980, and particularly tremendous deaths in developing countries.

Within the context of climate change adaptation, we coin the term “risk-mitigating innovation”, referring to the *development of new and more effective technologies that assist people in better coping with natural disasters and building resilience to future shocks*. Innovation is an important form of adaptation because it provides the technical methods for people to use in the process of adaption. While adaptation in some cases can be just behavioral changes, such as relocation, people more often have to employ certain technologies, which take either hard form (e.g., equipment and infrastructure such as building levees) or soft form (e.g., science, technical know-how, and skills such as emergency management) (UNFCC, 2006). 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 change the world’s ability to adapt to climate change. Innovation also includes improvement and commercialization of existing technologies, such as using new materials or new designs to make them more cost-effective in combating one or multiple types of hazards. As Ausubel notes in his 1991 article, technical innovation and diffusion related to climate change “occur in all societies and sectors and in many forms”. The importance of science and technology for climate adaptation has received increased attention in the international policy world (e.g., UNISDR, 2009; UNFCC, 2006), though this issue is often ignored in the research community. Our study contributes to a better understanding of the role of technologies in climate change adaptation.

Research on innovation has important implications for policymaking related to climate adaptation and disaster risk management. While adaptation is generally a local activity, innovation produces new knowledge and technologies that can often serve as a public good or even a global good. New technologies can be transferred and adopted by non-inventors and eventually benefit people and communities who face similar disaster risks. Therefore, introducing the concept of risk-mitigating innovation expands the conventional view on the highly localized nature of adaptation. From the policy perspective, encouraging risk-mitigating innovation and the transfer of these technologies can not only save the cost of repeated R&D elsewhere and improve the global equity in disaster risk reduction, but also can facilitate the knowledge spillovers and provide building blocks for persistent future innovations.[2]

This paper presents the first study to relate natural disaster impacts to technology innovation. In particular, we focus on three types of natural disasters, earthquakes, droughts and floods, and match each of them with one or two kinds of mitigation technologies including earthquake-proof building and earthquake detection technology, drought-resistant crop, and flood control technology.[3] Our analysis, using a panel of up to 30 countries over a period of 25 years, shows that all three types of natural disasters have a significant and positive impact on the patent counts of their corresponding technologies. Moreover, given the relative newness of adaptation as a climate change strategy, there has been very limited data and analyses done so far concerning the implementation of adaptation at a country or regional level. By using risk-mitigating innovation as an outcome of adaptation, our study also presents the first attempt to examine systematically the adaptation responses across multiple sectors at the country level.

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 focus on estimating costs or cost-effectiveness of adaptation

[2] Given the fact that most innovation activities are conducted in industrialized countries, their advanced technologies, if transferred properly, can benefit the developing countries, which not only lack the innovative capacity but also are more vulnerable to natural disasters relative to their developed counterparts.

[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 earthquake. Moreover, as researchers expect the probabilities of earthquakes to rise in certain regions (such as California) due to the crust movement, we believe earthquake fits neatly into the context of adaptation.

measures, at either the global level or at the country level, and many climate models simply treat adaptation as autonomous. For instance, recent examples of climate policy models incorporating adaptation are the AD-DICE model (deBruin *et al*. 2009), the WITCH model (Bosello, Carraro, and De Cian, 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, this paper also contributes to the literature of endogenous technological change by testing the impact of natural disasters as a stimulus for innovation.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 discusses a conceptual framework and lays out our key hypotheses. Section 4 describe the data sources and present some descriptive statistics. Section 5 discusses the empirical model and our results. Section 6 concludes.

## 2. Literature review

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 and Kellenberg and Mobarak, 2011). This literature primarily consists of two bodies of research, one concerning the economic effects of natural disasters, and the other assessing the determinants of natural disaster impacts (i.e., treating disaster damages as a function of natural and social factors). While our research falls into the first category, since we consider natural disasters as an explanatory variable, we also base our conceptual and empirical models partly on the second line of research which suggests that disaster impacts are endogenous.

Most empirical studies concerning the economic impacts of natural disasters (the first category) focus on assessing the costs of disasters or the impact of disaster shocks on output growth using macroeconomic indicators and sector-specific measures (e.g., Benson and Clay, 2004). This literature involves a subset of research that looks into the behavioral changes induced by natural disasters (e.g., how countries cope with the aftermath of disasters). Two recent studies of relevance in this aspect are Cuaresma et al. (2008) and Yang (2008). The first study tests the Shumpeterian theory of *creative destruction* (i.e., natural disasters that destroy capital stocks provide an incentive to update capital and employ newer technologies, thereby leading to higher productivities) by examining the relationship between disaster frequency and the R&D stocks embodied in the imports of developing countries. Using both cross-country and panel data regressions, they don't find any systematic evidence supporting such a positive link, except for high-GDP countries.[4] Yang (2008) examines the impact of hurricanes on a variety of types of international financial flows to developing countries. He finds that hurricanes lead to a significant increase in foreign aid as well as in migrants' remittances to the affected countries.

In this paper, we examine the incentivizing effect of natural disasters on the innovation of risk-mitigation technologies. Our research question implies at least two hypotheses: first, technological innovation can be driven by external factors and is thus endogenous; and second, disaster shocks can induce precautionary behaviors. To illustrate the two statements, we draw on and connect two separate strands of literature. First, the theory of induced innovation posits that changes in the relative price of an input of production leads to innovations that enable reducing

[4] Although Cuaresma et al (2008) also focuses on the link between natural disasters and technology, it should be noted that our research question is fundamentally different from theirs. 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 a on a specific group of technologies that can mitigate the risks of natural disasters.

use of the relatively more expensive factor (Hicks, 1932). Over the past decade, this theory has been increasingly applied to the field of environmental economics, as researchers try to understand the relationship between energy prices, environmental regulations and energy related innovations (for an overview of this topic see Popp, Newell, and Jaffe 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 innovation. 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). Our study adds to this literature on induced innovation by making the first attempt to link innovative activities to natural disaster events.

We also draw on the literature on risk perceptions and protection motivation to consider how disaster shocks encourage people to develop and adopt precautionary measures.  One key theoretical contribution in this field is the Roger's Protection Motivation Theory (Roger, 1983), which posits that people adjust their protective behavior based on their appraisal of external risks and appraisal of their own competence in coping with the threat. More specifically, the risk appraisal, or risk perception, involves the perceived probability of the occurrence of a threatening event occurrence and perceived severity of the threat. More recently, this theory has been used by environmental researchers to study individuals or households' adaptation motivation and behaviors. For example, Grothmann and Patt (2005) survey residents who face flooding risk in the city of Cologne, Germany and find that risk perception and perceived adaptive capacity play a more important role than socio-economic factors in explaining individuals' adaption decisions. With regard to the factors that affect risk perception, many researchers identify the prior disaster experiences/impacts as an important one. In a review of the natural hazards literature, Weinstein (1989) concludes that past experiences with natural disasters generally increase people's perception of risk and their preparedness, though such effects might be short-lived sometimes. Earlier studies (e.g., Perry & Lindell, 1986) find that prior disaster experiences involving only minor damages have little effect on risk perception and preparedness. This suggests that it is the severity of disaster impacts more than the disaster itself that determines people's risk perception.

Finally, we come back to the adaptation literature, which is a fast growing subfield of the contemporary natural disaster studies. The actual impact of a disaster falling on a community depends on the nature of the hazard as well as on local people's adaptation measures or their adaptive capacity (Yohe and Tol, 2002; Brooks et al, 2005; IPCC, 2012). In fact, increased attention has been focused on the term of adaptive capacity, an umbrella concept referring to a country/community's capability to undertake or develop adaptation (OECD, 2006; IPCC TAR, 2001). While there seems no clear consensus on the definition of the term, most researchers use "adaptive capacity" to summaries a set of social, economic and political characteristics that enable a society to mobilize its available resources to carry out adaptation.

In line with the notion of adaptive capacity is a series of empirical studies examining the determinants and heterogeneity of natural disaster impacts. By using a global cross-national data set on human mortalities from multiple types of natural disasters, Kahn (2005) shows that nations with higher income and more democratic institutions suffer fewer deaths from these disasters. His argument is that economic development and good institutions lead to better infrastructure and preventive technologies, more effective regulations and emergency management, which provide "implicit insurance" against natural disasters. Following Kahn's work, subsequent researchers use similar theoretical models and various measures of institution (e.g., inequality, corruption, political regime) to account for the cross-country heterogeneity in the impact of natural disasters. (Anbarci et al, 2005; Escaleras et al, 2006; Keefer et al, 2010). All of them offer strong evidence that good institutions can buffer natural disaster losses. The relationship between disaster losses and economic development was further examined by Toya and Skidmore (2007), Rashky (2008), Kellenberg and Mobarak (2008), Schumacher and Strobl (2011) and Hallegatte (2012). Rather than disaster losses decreasing monotonically with income, these studies show that the damage-income relationship also depends on the squared income level (Kellenberg and Mobarak, 2008), hazard exposure (Schumacher and Strobl , 2011) or the density of capital as risk (Hallegatte, 2012). In addition to income and institution, hazard exposure is another driving force for countries to adapt. For example, Hsiang and Narita (2012) find that countries with more intense tropical cyclones (TC) climates have lower marginal losses from an actual TC event, which provides direct evidence of adaptation. To sum up, this line of research reflects a consensus view that disaster impact is determined by both the exogenous natural hazards and local socioeconomic conditions. The implication for our study is that a disaster's impact (as an independent variable in our research) is influenced by any existing adaptation efforts, including a country's current adaptive capacity.

## 3. Conceptual framework

Drawing on the three lines of literature discussed above, we develop a conceptual framework for examining the effects of natural disaster on risk-mitigating innovations. Under this framework, the impact of a disaster shock potentially raises the perceived risks, and thereby leads to 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 disaster risks. To be consistent with the risk literature, we expect risk perceptions to depend on the severity of disaster impacts (e.g., human and economic losses from natural disasters) rather than simple counts or physical properties of disasters. The rationale is simple: if a natural disaster of extremely high magnitude occurs in an uninhabited area and results in little damage, it may not substantially affect people's risk perception. Our research question is essentially whether individuals react to these new events or whether the risks of natural disasters are properly perceived, so that new events do not change expectations.

We begin by modeling perceived risk $R^*_{it}$, which is unobserved, as a function of country *i*'s baseline hazard *H* (e.g. does the country have a fault line?), the country's capacity $C_{it}$ to cope with a disaster in year *t*, and the impact of current events $D_{it}$ (measured by death tolls or damages). The disaster impact in turn depends simultaneously on the magnitude of the exogenous disaster shock $M_{it}$ and the country's adaptive capacity $C_{it}$.

$$(1) \qquad R^*_{it} = f\{H_i, C_{it}, D_{it}(M_{it}, C_{it})\}$$

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% of all earthquakes occur in countries located along the "Ring of Fire" in the Pacific Ocean.[5] People living in these quake-prone countries presumably perceive stronger risks of earthquakes. 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 that significant damages will follow 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.[6]

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

[6] An analogy is the theory of "levee effect"(Stefanovic, 2003), which posits that people may excessively rely on the existing

Because capacity is not directly observed, we model capacity as a function of the following observed variables:

(2) $C^*_{it} = f(H_i, K_{i,t-1}, Y_{it}, I_{it})$.

As suggested by our literature review, both income, $Y_{it}$, and the quality of institutions, $I_{it}$, influence the coping capacity of a country. $K_{i,t-1}$, represents the current knowledge and technologies available to cope with the disaster in question. To the extent that previous events led to new innovations, there will be less need for additional innovation after a subsequent shock.

Finally, innovation itself depends on the perceived risk $R^*_{it}$ (and thus the demand for better technologies to cope with disasters), the existing knowledge base on which inventors can build $K_{i,t-1}$, income $Y_{it}$, and science policy $S_{it}$.

(3) $PAT_{it} = f(R^*_{it}, K_{i,t-1}, Y_{it}, S_{it})$

We use the count of patent applications pertaining to a given technology, $PAT_{it}$, to measure the outcome of innovative activities. Science policy 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 equations (1), (2), and (3) summarizes this reduced form relationship:

(4) $PAT_{it} = f(D_{it}, H_i, K_{i,t-1}, Y_{it}, I_{it}, S_{it})$.

Note that the effect of both economic development $Y_{it}$ and knowledge, $K_{i,t-1}$, are ambiguous. Equations (1) and (2) suggest that a greater existing knowledge stock and higher income increase adaptive capacity, thus reducing the need for additional innovation (because

protective measures knowing their existence. For example, people may think the construction of levees can fully protect themselves against all future floods.

perceived risk is lower).[7] At the same time, equation (3) suggests that existing knowledge serves as a building block for future innovation. While we expect a positive relationship between existing knowledge and innovation, it may also be the case that a strong existing stock may constrain technological opportunities and make future breakthroughs more difficult. Similarly, as innovation is primarily carried out in industrialized countries, and people from higher-income countries may have a higher demand for mitigation technologies, a positive correlation between GDP and patenting activity is also possible.

Equation (4) raises two issues for estimation. First, we consider potential lags between disaster events and patents. 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 changing climate. As such, we consider multiple lags when estimating our model.

Second, we must also consider how globalization renders countries increasingly interdependent with each other, so that a salient foreign disaster shock may generate a global effect in that it may raise the risk perception of the hazard in other countries.[8] One anecdotal example is that the Netherlands launched a full re-assessment of its risk management policy soon after Hurricane Katrina hit Louisiana, US in 2005. The global impact also includes technology spillovers, as advanced technologies developed in one country can be employed by the rest of the world to cope with their own disaster risks. In our baseline specification, year effects capture

[7] This suggests a learning-by-doing phenomenon, which we test in another paper which examines the effect of knowledge stocks in mitigating disaster risks.
[8] This "contagious effect" hypothesis has actually received some support in micro-level studies, as researchers find that indirect disaster experiences, which people obtain from observing disasters that happen to others, can also influence risk perception of those unaffected.

both the effect of these disasters on perceived risk and on the accumulation of global knowledge that may serve as a building block for domestic innovation. Later, we also directly assess the effect of foreign shocks and foreign knowledge stocks on domestic innovation by replacing the year fixed effects by such variables in our empirical analysis.

## 4. Data and Descriptive Statistics

In this study our dependent variable is the flow of risk-mitigating innovations, which is measured by the number of successful patent applications filed in a country in a given year. All our patent data is taken from an online global patent database Delphion.com and is identified through either International Patent Code (IPC) or key word searches (For a more detailed description of our patent search strategy, please see appendix 1). Given the issue of cross-country patenting (i.e., inventors can patent the same technology 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.

It is important to acknowledge that a patent, as a common measure of invention used in the innovation literature, is not a perfect measurement. Issues regarding using patent statistics to measure innovations were discussed by Griliches (1990) and Motohashi and Goto (2010). There are two major disadvantages 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. Since the propensity to patent varies by technology, we do separate regressions for each technology, so that 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 that the knowledge stock depends on a distributed lag of the current and past flows of innovations.

(5) $K_{it} = PAT_{it} + (1- \rho)\, K_{it-1}$

where $\rho$ is the rate of stock depreciation, which we assume to be 15 percent following the conventional innovation literature. Using a depreciation rate implies that 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, since most countries have zero patents in their first year of our estimation period.[9] For the ease of interpreting the effect of knowledge stock, we normalize this variable by taking log of the value of knowledge stock plus 1.

We measure disaster impacts, our key independent variable, using both human mortalities and economic losses from the natural disasters. Our disaster data on the three types of natural disasters (earthquake, drought and flood) is taken from two sources. We use the drought and flooding data from the Emergency Event Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disaster. Most current studies involving cross-country and multi-hazard analyses use the EM-DAT database. While this database is publically assessable, the accuracy of its data has been questioned given its humanitarian focus and specific thresholds for events to be included.[10] While we can identify no better alternative for information on flooding and droughts, we collect data on earthquakes from the National Geophysical Data

[9] 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, since a lot of countries in our sample have zero patents during the years. We feel safe to do so also because many countries have zero patents in their first year in our data set. Moreover, as our regressions begin in 1984 but our patent data begin in 1974, we have 10 years of historical data for most countries to construct the initial knowledge stock.

[10] EM-DAT includes events with either more than 10 fatalities, over 100 people affected, a declaration of a state of emergency, or a call for international assistance. It contains information on disaster events from 1900.

Center (NGDC) Significant Earthquake Database. This database is preferred to EM-DAT since 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. The economic losses are adjusted by the World Bank GDP deflator index.

In addition to the disaster impacts data, we also collect data to measure the magnitude of the exogenous disaster shocks, in order to instrument for potentially endogenous disaster impacts and knowledge stocks. For earthquakes, the NGDC database provides information such as the Richter scale of individual earthquake events. For drought, we use the Standardized Precipitation Evapotranspiration Index (Vicente-Serrano et al, 2010), which is a multi-scalar drought index that is calculated using precipitation and temperature data[11] and presented in a global gridded dataset at a spatial resolution of 0.5 degree (approximately 56 km x 56 km at the equator) covering the period of 1901 to 2009. This index is claimed to be "particularly suited to detecting, monitoring, and exploring the consequences of global warming on drought conditions" (Vicente-Serrano et al, 2010: p1698). Considering that drought is most likely to affect agriculture, we focus on the drought events occurring on cropland, and match the SPEI data with a global cropland coverage data set which is also at 0.5 spatial degree resolution.[12] Since out data is a panel structure of country by year, we use geospatial software to create a new country-year aggregate drought measure: we take the mean of the SPEI values which are under 0 (indicating dryness) with their feature points (defined by longitude and latitude) located on cropland.[13] For flood, we use the area-weighted-precipitation data from Dell et al (2012) and assume that

[11] Their original weather data is taken from the Global Historical Climatology Network database.
[12] The global cropland dataset, which spans from 1700 to 2007, is produced by Navin Ramankutty at the Land Use and the Global Environment lab of Mcgill University.
The data is retrieved from http://www.geog.mcgill.ca/~nramankutty/Datasets/Datasets.html
[13] In the original global cropland data, for each feature point cropland is identified by a crop coverage percentage. To simplify our definition of cropland, we calculate the mean cropland coverage ratio by country-year and treat all feature points which exceed the country mean in the same year as cropland.

excessive rainfall is often an exogenous shock causing flooding.[14]

For data on country characteristics, we use the data on real GDP per capita and population from Penn World Table (7.0 version). To measure institutional quality, we use the polity variable from POLITY IV project, which takes on the value from -10 to 10 and indicates a country's openness of political institution (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 by a country's residents to control for this country characteristic. This data comes from the World Bank World Development Indicators and the database of the World Intellectual Property Organization.

In this study, we look at three types of natural disasters and four different types of technologies. For each technology, we construct a sample of countries with the selection criteria that the country should have at least five patents in a given technology field between 1974 and 2009. We begin in 1974 because patent data for many countries first appears in the Delphion database in the mid-1970s. Therefore, our sample size varies according to different technology types. Appendix 2 lists the countries included for each technology.

Table 1 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 a 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), since they have higher demand and more resources for science, technology and innovation. In particular, United States, Germany and Japan appear to

[14] The precipitation data in Dell et al (2012) have also been aggregated to the country-year level. The original data is taken from the Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01(Matsurra and Willmott 2007).

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 disaster types, earthquakes and floods cause much larger losses on our sample countries than droughts. This suggests that two possibilities. First, while droughts will typically affect a larger geographic area than earthquakes or floods, their impact is primarily on a single sector (agriculture), rather than the entire economy of the affected area. Second, given that most of our sample countries are developed countries, they already have good technologies and infrastructure such as irrigation systems which make them less vulnerable to drought. In fact, the statistics of global drought impacts by country (based on the EM-DAT data) shows that most of the severe drought events in the past forty years have occurred in developing nations, in particular the least developed countries in Africa.[15] This fact further confirms that the impact of drought highly depends on an area's vulnerability or adaptive capacity.

Figures 1-3 illustrate trends in patenting behavior for selected countries, with major disaster events also highlighted. Figure 1 shows earthquake mitigation patenting trends for the United States and Japan. In both cases, patenting activity increases after major earthquakes, such as the 1989 Loma Prieta earthquake in the U.S. and the 1995 earthquake in Kobe, Japan. Figure 2 shows similar trends for flood control technology in the Unites States and United Kingdom. In contrast, a visual inspection of drought-resistant crop technologies suggests a more gradual increase in patenting activity over time. Possible explanations include increased awareness of drought risks from climate change or increased patenting due to advances in agricultural

[15] We rank countries that are most often hit by drought from 1970 to 2010 using the drought data from EM-DAT. Only five countries in the top 15 (China, Brazil, Australia, India, United States) are included in our sample. The other countries are Mozambique, Ethiopia, Kenya, Bolivia, Somalia, Honduras, Indonesia, Mauritania, Philippines, and Sudan, which have no patents in either of the drought-mitigating technologies.

biotechnology. Year effects in the regression analysis allow us to control for both possibilities.

Table 2 presents the descriptive statistics of main variables in the analysis. It should be noted that though our patent data generally becomes available in 1974, we deliberately choose to start our estimation period at least 10 years later because we have the knowledge stock, which is also a function of patent counts, on the right hand side. In this way, we allow the stock to accumulate for ten years before it enters into the estimation equation.

## 5. Empirical model and main results

### 5.1 Domestic disaster impacts

To examine the relationship between disaster shocks and risk-mitigating innovations, we estimate a reduced-form empirical model based on our proposed conceptual framework:

$$(6) \quad PAT_{jit} = f\left(\sum_{n=0}^{5} D_{it-n},\ Y_{it},\ I_{it},\ K_{jit-1},\ S_{it},\ \eta_i,\ \phi_t\right)$$

where the innovation flow ($PAT_{jit}$) is the total number of successful patents in the technology field $j$ applied by the residents in country $i$ in year $t$. It is the function of contemporary and lagged impact of natural disasters that occurred in country $i$ and a set of country characteristics including real GDP per capita $Y_{it}$, political institutions $I_{it}$, existing domestic knowledge stock relevant to the specific technology type in question, $K_{jit-1}$, and general patent application quantity $S_{it}$. The reason for using a distributed lag of disaster impacts is that we are reluctant to impose a structure on the effects of recent year's disasters on innovation.[16] Country fixed effects $\eta_i$, control for time-invariant heterogeneity across country (e.g., the baseline hazard risks,

[16] As we discussed earlier, innovation takes time. Whether the most recent disasters have bigger impacts on innovative activities is an empirical question. To determine the number of year lags to be included in the regression, we first conduct a sensitivity test by gradually increasing the lags. We find the coefficients on lagged values of disaster effects generally become insignificant beyond five years ago. Further sensitivity analysis of the lags is available in Appendices 3 and 4.

innovation capacity, and other unobserved country specific characteristics), and also helps to address the potential endogeneity of the disaster impact variables. Year fixed effects $\phi_t$ control for time-varying factors common to all countries (e.g., the global technology advancement, salient disaster shocks which occurred in one country but affect the global risk perception).

Given the count-data nature of our dependent variable (i.e., patent counts) and panel nature of our data structure, we use Poisson fixed-effects model with robust standard errors to address possible over-dispersion in the data (Cameron and Trivedi, 2005). Standard errors are clustered by country.[17] We use the fixed-effects model because the unobserved heterogeneity across countries as discussed above is very likely to exist and correlate with the explanatory variables.[18]

We estimate our empirical model by using the Generalized Methods of Moments (GMM) technique (Hansen, 1982). While this estimation equation allows the individual effects to correlate with the other regressors, the consistency of the estimators rely on the assumption of strict exogeneity of explanatory variables (E($x_{it}u_{it}$) = 0). In other words, the regressors must not correlate with any of the past, current and future error terms. However, this assumption seems difficult to justify in our model for two reasons. First, our lagged knowledge stock variable is constructed using a distributed lag of previous patent counts, and therefore has the similar character of a lagged dependent variable, which is predetermined. Second, the disaster impacts may also be predetermined in the sense that the earlier efforts of innovating as a response to past disaster shocks may help alleviate the human mortalities and economic losses of the subsequent similar events. It should also be noted that the inclusion of country fixed effects is to capture the

[17] Because of the panel nature of the data, we do not use a negative binomial model, as the negative binomial fixed effect model does not truly control for unobserved fixed effects (Alison and Waterman, 2002; Cameron and Trividi 2005; Paulo 2008).
[18] 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 $\eta_i$ with the other regressors would make a standard random effects estimator inconsistent.

time-invariant individual effects that may affect innovation motivation and patenting. If the time-varying elements of a country's adaptive capacity that may affect disaster outcomes are not fully accounted for, this might also induce the endogeneity issue of our disaster variables.

To address these issues, we estimate two specifications. First, we replace the $K_{jit-1}$ in the estimation equation (6) with $K_{jit-6,}$ so that the knowledge stock is no longer a function of the lagged disaster impact variables in our regression and can be treated as exogenous to today's innovation flows. Using this specification we essentially assess the effect of disaster events that occurred in the present year as well as in the last five years on risk-mitigating innovation, considering that they may both induce innovation today to do lagged reactions and may reduce the need for innovation due to earlier improvements to adaptive capacity in the past five years in reaction to lagged disasters. One caveat is that the reduced form specification does not address the issue of strict exogeneity. Given the long time frame of our sample, such concerns are unlikely to cause significant bias, and this specification does not suffer if potential instruments, described below, are weak (Wooldridge 2010).[19]

Second, we use the instrumental variable approach, using the magnitude measures of shock events that have induced natural disasters as instruments. Our argument is that the "natural destructiveness" of a disaster correlates directly with the disaster outcomes such as human and economic losses and should be exogenous. Moreover, since our theory posits that disasters induce innovation and subsequent accumulation of the specific technical knowledge to cope with disasters, the magnitude measures should also exert a positive effect on the knowledge stock. Therefore, in addition to using the disaster magnitude that corresponds to each year's disaster impact, we instrument for knowledge stock using the magnitude information over a

[19] When strict exogeneity is violated, the bias is a function of $1/T$. Our regressions include 24-26 years of data, so that any potential bias is scaled by a factor of approximately 0.04.

longer period of 25 years, given the availability of rich pre-sample data. By instrumenting for the lagged knowledge stock, the second specification allows us to directly interpret the effect of the existing knowledge base on upcoming innovations. For some types of technology (e.g., earthquake mitigating innovations), we also use a country's population as an instrument for disaster impacts because a high density of population is presumably more subject to human and economic losses when being hit by a disaster shock.[20] One complication for earthquake is that our unit of analysis is country-year instead of events. We use two variables to measure the severity of earthquakes, the maximum earthquake magnitude if any occurs in a country-year and the total number of earthquakes with a magnitude six or large in a country-year. As for drought, we use the aggregated Standardized Precipitation Evapotranspiration Index (SPEI) at country-year level as well as population to instrument for drought damages and lagged knowledge stocks. The instrument we use in the case of flooding is area-weighted precipitation (Dell et al, 2012) for country-year. In all cases, the instrumental variable approach provides consistent estimates of our parameters as long as the quality of our instruments is good. However, the results suffer if the instruments are not strong predictors of disaster impacts and lagged knowledge.

Table 3 presents the estimation results for both specifications using death tolls as the measure of disaster impact. Note that for droughts we focus on only economic damage because a majority of our sample countries have zero deaths over the estimation period. Income and total patent applications are in logs, so that the coefficients can be interpreted as elasticities. The results show that human mortalities from recent disasters generally have a significant and positive effect on the domestic patent flows for all technologies concerned. Such evidence

[20] To address the predetermined and 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 can not only allow 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 (weak instrument problem). We have found the same problem when we applied this approach to our data.

supports our principal hypothesis that natural disasters lead to risk-mitigating innovations, and the amount of successful patent applications following disaster events increase with the severity of disaster impacts. Specifically, in the case of earthquakes, the coefficients on the current-year's death (measured in thousand) suggest that an additional 1,000 deaths increases the expected counts of patents of earthquake-proof building and detection technology applied for in same year by 1.3% - 1.5%, respectively.[21] Comparing the two types of earthquake-mitigating technologies, we find that earthquake impacts seem to have a long-term effect on quake-resistant building patents while its effect on detection patents seems more immediate (i.e., only the coefficients on the present year and last year's death are statistically significant). The row "sum of death" presents the joint significance of all current and lagged impacts. For quake-proof buildings, one thousand deaths from earthquakes can increase the expected counts of patents filed in the next five years by about 18.6 – 23.8%, while such impact on the detection patents are insignificant over the five-year period. It is somehow surprising to see the lagged effect does not become smaller with the increase of year lags, as reflected in the magnitude of the coefficients. One possible explanation is that the innovation of earthquake-proof buildings is not only stimulated by the disaster events but also subject to the changes in regulations (e.g., building codes may be revised following severe events, thereby providing a long-term motive for innovation). By comparing the two different specifications, we notice that the significance of most coefficients does not change much, and the coefficient magnitudes of those highly significant variables are largely similar.[22]

[21] As we use Poisson model for estimation, we are able to interpret the coefficients in a semi-elasticity form.

[22] However, recall that we should be cautious about the difference in how to interpret these coefficients, since we are controlling for two different levels of lagged knowledge stock in the two models. In specification (1), we estimate the effect of recent disasters conditioning on the six-year lagged knowledge stock (that had been established before these events actually happened); and in specification (2), we estimate the effect of a distributed lag of disasters controlling for last year's knowledge stock, so the effect of earlier disaster events (e.g., year t-5) on existing knowledge will already be captured in the knowledge stock variable. In Appendix 5, we demonstrate that this has little impact on the magnitude of the individual coefficients.

As for flood-control technology, we only show the results for specification 1 because the instrument (i.e., area-weighted precipitation) is weakly correlated with the death variables.[23] The results shows that the cumulative effects of recent flooding events on the innovation of flood-control technologies in particularly prominent: an additional 1,000 deaths from floods that have occurred in the past five years plus the present year would lead to an increase of patent application in this field by 88%. Also, the six-year lagged knowledge stock is statistically significant and positive for patent counts: a ten percent increase in the knowledge stock of six years ago is associated with 2.5% 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-mitigating innovations as part of a country's existing adaptive capacity.

Table 4 reports the estimation results using economic losses as a measure of disaster impact for both specifications. The results are largely consistent with what we have found using human losses, that is, economic damages from recent disasters generally have a statistically significant and positive effect on the innovation of risk-mitigation technologies. As for earthquakes, the pattern of the disasters-innovation relationship is somewhat similar with that in Table 3: patenting in earthquake-proof building technology seem to be more affected by the earlier events (though it should be noted that in specification 2, the coefficient on current year's damage turns significant with a much large magnitude compared to that in specification 1), while patenting of earthquake detection technology is more responsive to the most recent events. We also notice that when instrumenting for disaster impacts (specification 2), the coefficients on one-year lagged knowledge stock for both two technologies are positive and significant at 5% level, which suggests that the supply-side effect of the existing knowledge base on upcoming

[23] Appendix 6 provides information on the fit of the instruments for each of our technologies and endogenous variables.

innovations may play a dominant role. As for flooding, the stimulating effect of disasters on patenting seems to come more from recent years, and both specifications show that the magnitude of such impact is biggest for the current year's flooding: an additional $1 billion economic loss would increases the expected number of flood-control patent applications filed in the same year by 4.8% - 11%. The effect of the lagged knowledge stock seems ambiguous in this case: although both two have positive coefficients, neither is significant at 5% level. As for the drought-resistant crop technology, the effect of drought on patenting activities is also positive and statistically significant in most lagged years (except year *t*-1 and *t*-3) in the specification 1. It is estimated that an additional $1 billion economic losses from drought that occurred no earlier than five years ago would increase the expected number of patent applications filed at the present year by approximately 20%. When we instrument for drought damage using aggregated drought index, the coefficient of the present year's damage has been substantially inflated to 0.244 (this suggests the immediate innovation response is even larger than the long-term responses in the specification 1), while coefficients on other lagged years turn insignificant. It is also surprising to see that the coefficients on other country controls, such as GDP, institution quality and general patent applications, are very different from those in specification 1. In particular, the control for total patent applications has an unexpected negative sign in this specification. We suspect these problems are the results of the relatively weak link between our instruments and the damage variables, as discussed in Appendix 6. Given that there are few differences between specifications 1 and 2 for other technologies, we place more faith in specification 1 for drought-resistant crops.

## 5.2 Do foreign shocks matter?

So far we have examined the effect of domestic disaster shocks on domestic innovation of risk-mitigating technologies. Here we consider whether innovators also respond to salient foreign disaster shocks and whether they could benefit from the adaptive knowledge that has been created abroad (i.e., knowledge spillover effects). To answer this question, we create variables measuring the impact of foreign shocks as well as foreign knowledge stocks and use them to replace the year fixed effects to avoid multicollinearity.[24] Specifically, we estimate the following model:[25]

$$(7) \quad PAT_{jit} = f\left(\sum_{n=0}^{5} DD_{it-n}\,,\ \sum_{n=0}^{5} FD_{it-n}\,,\ DK_{jit\text{-}6}\,,\ FK_{jit\text{-}6}\,,\ Y_{it}\,,\ I_{it}\,,\ S_{it}\,,\ \eta_i\right)$$

in which $DD_{it}$ denotes the human mortality or economic losses resulting from natural disasters that occurred in country *i* in year *t*, while $FD_{it}$ is the human or economic losses from disasters that occurred outside country *i* in year *t*. $DK_{jit\text{-}6}$ denotes the domestic knowledge stock in technology field *j* in country *i* by year *t*-6. $FK_{it\text{-}6}$ denotes the foreign knowledge stock constructed by the patents filed outside country *i* up until year *t*-6.

Table 5 reports the estimation results. First, removing the year fixed effects and adding controls for foreign disasters and knowledge increases the significance of some coefficients on the distributed lag of domestic disasters. But this does not affect the cumulative effect of domestic shocks much, which suggests the robustness of our estimation. In terms of foreign impact, we find foreign disasters that have occurred between year *t* and year *t*-5 together exert a

[24] To create the foreign impact variables, we first calculate the total global impacts by aggregating the human or economic losses from all countries in the database (not limited to our sample countries) and subtract each country's own losses from the total global losses. We construct the foreign knowledge stock in the same way as we create the domestic knowledge stock (using the perpetual inventory model). We aggregate the total number of patents filed in the world in a year and then subtract each country's own patents from the global pool to obtain the foreign patent counts by country-year.

[25] Note that model (7) is largely based on specification (1), which uses country fixed effects and no instrument variables. We choose this to derive our foreign model due to the small difference between this approach and the instrument approach.

statistically significant and positive effect on the domestic innovation of flood control and drought-resistant crop technology, though the magnitude of such effect is much smaller compared to the domestic disasters. Surprising, the patent counts of quake-proof technology decrease with the severity of foreign earthquakes, and this effect is statistically significant at 1% level for most lagged-year coefficients when severity is measured by deaths. While it may simply be that innovation of building technology might be primarily driven by domestic demand and institutions (e.g., building codes) and less subject to the foreign disaster shocks, we cannot rule out that the lack of year fixed effects may imply an omitted variable correlated with foreign disasters. For detection technology, the innovative response to foreign earthquakes seems more immediate and only significant in the current year. This pattern is consistent with the response to domestic earthquakes, while the magnitude of foreign effects is also very small. In terms of the knowledge spillover effects, we find that for earthquake detection and drought-resistant crop, foreign knowledge stocks lagged by six years have a significant and positive effect on domestic innovation, which suggests the potential spillovers across countries.

In addition to not controlling for year effects, the previous model also assumes that all global disasters have a similar impact on innovation. We next relax this assumption, asking whether disaster shocks that occur in nearby foreign countries would more likely induce domestic innovation of risk-mitigating technologies. The rationale is that geographic proximity leads countries to share some similar geophysical characteristics, thereby causing risk perception to be influenced by the incidence of one another. Moreover, geographic proximity might imply a potential same market and make it easy for foreign technologies to diffuse and profit. To test this hypothesis, we group countries by continent and create variables of foreign disaster impact based on the same continent external to country *i*. By adding more cross-country variation to foreign disasters, we are also able to once again include year fixed effects, so that year dummies can capture global technological progress, salient global shocks, and any potential omitted variables correlated with such shocks. Other variables remain the same.

Table 6 reports the estimation results using this approach. Again, the coefficients on the distributed lag of domestic disaster impact largely stay the same as compared to the original domestic model. Foreign disasters that occurred between year *t* and *t*-5 on the same continent external to a country have a positive cumulative effect on its domestic innovation of detection and flood control technology, and such effect is statistically significant when foreign impact is measured by death for detection and damage for flood control. For quake-proof building technology, using this new measure makes some originally negative coefficients on foreign shocks in model (7) no longer significant. But we still see no evidence on the link between foreign disasters and domestic innovation for this technology. Finally, unlike when controlling for all foreign damages, foreign disaster impacts generally are now insignificant for drought-resistant crop technology. One possible explanation is the presence of the global crop market and the concentration of innovative activities by a few biotech multinational corporations. To summarize, we do find some evidence suggesting the impact of foreign shocks and foreign knowledge spillovers on domestic innovation, though such evidence is not pervasive across all technology types.

## 6. Conclusion

Natural disasters cause tremendous human causalities, as well as significant economic losses worldwide. But apart from this, what do people learn from suffering natural disasters? Do they improve their coping capacity every time after being hit by a disaster shock? These are meaningful questions for both researchers and policy makers to consider. Until now, there has been no systematic study of the role of technology and innovation in climate change adaptation. This paper fills this gap, linking three types of natural disasters (earthquakes, droughts, and flooding) to a set of mitigation technologies.

By introducing the idea of "risk-mitigating innovation", we conceptualize innovation as an important form of adaptation. We bring together two lines of research on induced innovation and adaptation to develop a conceptual framework for assessing the effects of natural disasters on risk-mitigating innovation. Our empirical analysis, using a panel of up to 30 countries covering a period of about 25 years, reveals a consistent stimulating effect of natural disasters on patent flows of the technologies that can mitigate similar disaster risks. For all types of technologies concerned here, we find evidence that the amount of risk-mitigating innovation in a country increases with the severity of its recent natural disasters. This finding suggests that people are constantly learning from their disaster experiences, though they adapt to natural disasters in a reactive manner. This has important implications for both policymakers and modelers of climate policy, as it suggests that 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.

Moreover, our study also shows that innovators not only respond to domestic shocks but also respond to natural disasters occurring in other countries, although the magnitude of the latter is much smaller and the link is not pervasive across all technology types. We also find that the growing pool of global knowledge on disaster mitigation exerts a stimulating effect on domestic risk-mitigating innovation (e.g., for earthquake detection and drought-resistant crop technology).

This finding has important implication for global adaptation policy making. Since most of the innovative activities are currently taking place in industrialized countries, their risk-mitigating innovation can generate positive externalities to the developing world and could be translated into useful local knowledge to cope with natural disasters and reduce vulnerability. Policies are needed to facilitate the transfer of more risk-mitigating technologies to countries with limited technological resource and capacity and deployment of these technologies.

As the first study integrating technology innovation and adaptation, we believe that this line of research can be further extended in at least two directions. First, in this study we construct the measure of foreign disaster shocks and foreign knowledge stocks in a relatively coarse way. In fact, not all natural disasters that have occurred elsewhere in the world or foreign knowledge available are relevant for a country.  More detailed analyses could be done in this regard, for example, weighing the foreign impacts by geographic distance between countries and measuring the existing foreign knowledge stock using the patent family and patent citation information. Second, more research could be done to assess the role of technological change in facilitating adaptation to climate change. In this study we mainly focus on how natural disasters induce risk-mitigating innovation, but we have little to say about the effectiveness of these new innovations in reducing disaster risks (e.g., saving lives and preventing economic losses). Particularly, given the public good nature of knowledge, it is an important policy and research question to gauge the potential benefits of diffusion of risk-mitigating technologies in the global context.

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## Table 1- Natural Disaster and Patent Statistics for Sample Nations, 1970-2009

| **Disasters** | **Earthquake** | | | | **Drought** | | | **Flood** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| *Technology* | *Quake-proof Building* | | *Detection* | | *Drought-resistant* | | | *Flood Control* | | |
| Country | Average deaths per year | Average damages per year | Total patent counts | Total patent counts | Average deaths per year | Average damages per year | Total patent counts | Average deaths per year | Average damages per year | Total patent counts |
| Argentina | 1.93 | 5.50 | 10 | . | . | . | . | . | . | . |
| Australia | 0.30 | 0.17 | 12 | . | 0 | 405.93 | 39 | 5.08 | 116.28 | 10 |
| Austria | 0.03 | 0 | 7 | . | 0 | 0 | 6 | 0.975 | 96.13 | 5 |
| Belarus | 0 | 0 | 8 | . | . | . | . | . | . | . |
| Belgium | 0.05 | 2.17 | 8 | . | 0 | 0 | 22 | . | . | . |
| Brazil | . | . | . | . | 0.5 | 214.86 | 5 | . | . | . |
| Bulgaria | 0.08 | 0.2 | 8 | . | . | . | . | . | . | . |
| Canada | 0 | 0 | 35 | 12 | 0 | 270.53 | 39 | 0.925 | 64.22 | 16 |
| China | 9055.73 | 3347.25 | 291 | 748 | 88.35 | 685.72 | 636 | 949.33 | 4140.81 | 305 |
| Czech Republic | . | . | . | . | . | . | . | 2.18 | 150.59 | 46 |
| East Germany | . | . | . | . | 0 | 0 | 12 | . | . | . |
| Denmark | 0 | 0 | 6 | . | 0 | 24.53 | . | . | . | . |
| France | 0.23 | 0 | 134 | 28 | 0 | 57.78 | 46 | 4.75 | 157.69 | 34 |
| Germany | 0 | 9.28 | 149 | 20 | 0 | 0 | 182 | 1.08 | 375.95 | 227 |
| Greece | 6.78 | 107.88 | 31 | 12 | . | . | . | . | . | . |
| Hungary | 0 | 0 | 11 | . | 0 | 35.03 | 10 | 7.73 | 21.173 | 10 |
| India | . | . | . | . | 8.8889 | 78.36 | 7 | . | . | . |
| Israel | 0 | 0 | . | 8 | 0 | 2.16 | 23 | . | . | . |
| Italy | 152.75 | 1520.69 | 42 | 6 | 0 | 0.0263 | . | 14.43 | 634.39 | 9 |
| Japan | 154.73 | 4211.90 | 9928 | 1344 | 0 | 0 | 93 | 28.15 | 329.41 | 415 |
| Mexico | 266.00 | 175.51 | 10 | . | 0 | 47.71 | 5 | . | . | . |
| Netherlands, The | 0.03 | 3.26 | 11 | . | 0 | 0 | 18 | 0.03 | 18.07 | 8 |
| Norway | . | . | . | . | 0 | 0 | . | . | . | . |
| New Zealand | 0.08 | 8.10 | 29 | . | 0 | 3.13 | 12 | . | . | . |
| Poland | 0 | 0 | 13 | . | . | . | . | 2.35 | 146.64 | 22 |
| Republic of Korea | 0 | 0 | 217 | 27 | 0 | 0 | 48 | 57.1 | 91.14 | 187 |
| Romania | 39.98 | 82.73 | 23 | . | . | . | . | 16.7 | 105.69 | 7 |
| Russia | 100.93 | 753.50 | 79 | 126 | 0 | 0 | 16 | 13.58 | 68.50 | 61 |
| Saudi Arabia | . | . | . | . | 0 | 0 | . | . | . | . |
| Singapore | . | . | . | . | 0 | 0 | . | . | . | . |
| South Africa | . | . | . | . | 0 | 33.41 | . | . | . | . |
| Soviet Union (Former) | 1126.95 | 1229.65 | 385 | 47 | 0 | 0 | 60 | 6.73 | 214.86 | 11 |
| Spain | 0 | 1.27 | 25 | . | 0 | 396.07 | 8 | . | . | . |
| Sweden | 0 | 0 | 6 | . | 0 | 0 | . | 0.28 | 11.49 | 10 |
| Switzerland | 0 | 0 | 12 | . | 0 | 0 | 13 | 0.25 | 72.26 | 13 |
| Taiwan | 58.60 | 403.05 | 97 | 27 | 0 | 0 | . | 2.7 | 6.71 | 18 |
| Ukraine | 0 | 0 | 217 | 5 | . | . | . | . | . | . |
| United Kingdom | 0 | 0 | 33 | 7 | 0 | 0 | 15 | 1.23 | 415.47 | 89 |
| United States | 5.68 | 1406.02 | 323 | 125 | 0 | 203.80 | 864 | 35.5 | 1356.8 | 91 |

All the economic losses are in million US dollars (2005 level). 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 that these countries have never been hit by any disasters.

**Table 2 - Descriptive Statistics**

| **Disaster Type** | **Earthquake** | | | | **Drought** | | **Flood** | |
|---|---|---|---|---|---|---|---|---|
| *Technology Type* | *Quake-proof building* | | *Earthquake Detection* | | *Drought-resistant Crop* | | *Flood Control* | |
| **Dependent variable** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** | **Mean** | **Std. Dev.** |
| Patent counts | 15.21 | 72.74 | 6.57 | 19.80 | 4.21 | 14.03 | 3.14 | 6.55 |
| **Independent variables** | | | | | | | | |
| Deaths (thousand) | 0.18 | 3.33 | 0.34 | 4.74 | 0.01 | 0.10 | 0.06 | 0.34 |
| Foreign deaths (thousand) | 14.63 | 23.70 | 23.21 | 46.88 | 0.30 | 0.53 | 7.10 | 6.10 |
| Damages (2005 US$, billion) | 0.56 | 7.47 | 1.12 | 10.66 | 0.11 | 0.86 | 0.66 | 2.72 |
| Foreign damages (2005 US$, billion) | 18.67 | 37.95 | 17.99 | 37.11 | 3.06 | 3.92 | 18.47 | 12.00 |
| Log domestic knowledge stock | 1.99 | 1.58 | 1.87 | 1.60 | 1.34 | 1.38 | 1.60 | 1.37 |
| Log foreign knowledge stock | 7.54 | 0.65 | 5.75 | 0.66 | 5.02 | 1.14 | 5.21 | 0.91 |
| Real GDP per capita (2005 US$, thousand) | 21.42 | 10.75 | 22.44 | 11.09 | 22.44 | 11.03 | 23.67 | 10.62 |
| Institution index (-10~10) | 7.33 | 5.18 | 7.81 | 4.68 | 7.69 | 4.85 | 7.78 | 4.80 |
| Patent application counts (thousand) | 27.20 | 69.87 | 34.84 | 78.86 | 34.54 | 78.26 | 39.42 | 82.57 |
| Population (million) | 88.54 | 223.77 | 161.11 | 312.42 | 160.14 | 310.31 | 114.33 | 264.70 |
| Maximum Earthquake Magnitude | 1.63 | 2.83 | 2.48 | 3.19 | | | | |
| Count of earthquakes (>=6) | 0.32 | 0.88 | 0.55 | 1.15 | | | | |
| Aggregated Drought Impact Index | | | | | 0.73 | 0.60 | | |
| Area-weighted Precipitation (mm) | | | | | | | 67.86 | 34.61 |
| *Number of countries* | 30 | | 15 | | 23 | | 21 | |
| *Timespan* | 1984-2009 | | 1984-2009 | | 1984-2009 | | 1986-2009 | |

**Table 3. Regression Results in Response to Deaths**

| Technology | Quake-proof building | | Earthquake detection | | Flood control |
|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) |
| Death | 0.0149*** | 0.0139*** | 0.0130*** | 0.0131*** | 0.214** |
| | (0.00540) | (0.00368) | (0.00224) | (0.000690) | (0.0986) |
| L1.death | 0.00821 | 0.000765 | 0.00951*** | 0.0102*** | 0.131** |
| | (0.00653) | (0.00695) | (0.00248) | (0.00111) | (0.0620) |
| L2.death | 0.0242* | -0.00177 | -0.00736 | 0.0539 | 0.312*** |
| | (0.0130) | (0.0556) | (0.0221) | (0.0561) | (0.0968) |
| L3.death | 0.0123 | 0.106 | -0.00297 | 0.101 | 0.120* |
| | (0.0183) | (0.0909) | (0.0203) | (0.142) | (0.0650) |
| L4.death | 0.0471 | 0.0182 | -0.0546 | 0.0154 | 0.0107 |
| | (0.0336) | (0.0569) | (0.0652) | (0.0886) | (0.0434) |
| L5.death | 0.0800*** | 0.101** | -0.104 | -0.0767*** | 0.0958 |
| | (0.0209) | (0.0395) | (0.0674) | (0.0135) | (0.0706) |
| Sum of deaths | 0.18669*** | 0.23855*** | -.146725 | 0.1168832 | 0.8841*** |
| | (0.56063) | (0.083) | (0.13317) | (0.25461) | (0.23391) |
| L6. Log stock | 0.265 | | -0.262 | | 0.254*** |
| | (0.224) | | (0.166) | | (0.0891) |
| L1. Log stock | | 0.662* | | 0.0163 | |
| | | (0.354) | | (0.291) | |
| Log GDP per capita | 1.904* | 2.703** | 0.622 | 2.077 | 1.845** |
| | (1.056) | (1.073) | (1.082) | (1.807) | (0.825) |
| Institution index | 0.00817 | 0.121 | 0.0941 | 0.0743 | 0.297** |
| | (0.0622) | (0.114) | (0.110) | (0.152) | (0.135) |
| Log Patent applications | 0.317* | -0.345 | 0.343 | -0.383 | 0.286 |
| | (0.179) | (0.311) | (0.413) | (0.594) | (0.250) |
| Observations | 717 | 703 | 338 | 327 | 459 |
| Countries | 30 | 30 | 15 | 15 | 21 |
| E(Q) | 0.0000 | 0.0827 | 0.0000 | 0.2053 | 0.0000 |
| Timespan | 1984-2009 | 1984-2009 | 1984-2009 | 1984-2009 | 1986-2009 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

Deaths are measured by 1000 people. The instruments we use in the specification (2) for quake-proof building and earthquake detection technologies include the maximum earthquake magnitude and counts of earthquakes with magnitude 6 or larger in year t to year t-25, and population in year t to year t-5.

**Table 4. Regression Results in Response to Damages**

| Technology | Quake-proof building | | Detection | | Flood control | | Drought-resistant crop | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Damage | 0.00443 | 0.0124*** | 0.00847*** | 0.0119** | 0.0476*** | 0.111** | 0.0659*** | 0.175** |
| | (0.00380) | (0.00193) | (0.00189) | (0.00090 | (0.0123) | (0.0462) | (0.0140) | (0.0714) |
| L1.damage | 0.00322 | 0.00336 | 0.00461*** | 0.00823* | 0.0414*** | 0.0442** | 0.0177 | -0.0358 |
| | (0.00196) | (0.00223) | (0.00172) | (0.00106) | (0.0157) | (0.0185) | (0.0209) | (0.0670) |
| L2.damage | 0.00286** | 0.00133 | 0.00358* | 0.00583* | 0.0323*** | 0.0309 | 0.0514*** | 0.0120 |
| | (0.00144) | (0.00135) | (0.00198) | (0.00265) | (0.00954) | (0.0643) | (0.0197) | (0.0460) |
| L3.damage | 0.00474*** | 0.00324 | 0.000752 | 0.00275 | 0.0111 | 0.0473 | 0.00771 | -0.0486 |
| | (0.00100) | (0.00310) | (0.00318) | (0.00455) | (0.00948) | (0.0376) | (0.0124) | (0.0949) |
| L4.damage | 0.00280** | 0.00110 | 0.000666 | 0.00431 | 0.0121* | -0.0898** | 0.0246*** | -0.0846 |
| | (0.00133) | (0.00152) | (0.00230) | (0.00290) | (0.00681) | (0.0408) | (0.00806) | (0.0577) |
| L5.damage | 0.00297*** | 0.00332** | -0.00295 | 0.00527* | 0.00492 | 0.0719 | 0.0346*** | -0.00908 |
| | (0.00101) | (0.00135) | (0.00227) | (0.00226) | (0.00497) | (0.0490) | (0.00907) | (0.0228) |
| Sum of damages | 0.02102*** | 0 .0248*** | 0.01513 | 0.025557 | 0.14947** | 0.21493 | 0.202 | 0.009 |
| | (0.00813) | (0.00479) | (0.01153) | (0.00934) | (0.05297) | (0.20379) | 0.0624 | 0.1204 |
| L6. Log stock | 0.195 | | -0.129 | | 0.146* | | -0.0181 | |
| | (0.222) | | (0.245) | | (0.0768) | | (0.125) | |
| L1. Log stock | | 0.565** | | 0.584** | | 0.104 | | 0.685*** |
| | | (0.242) | | (0.271) | | (0.343) | | (0.241) |
| Log GDP per capita | 1.710** | 1.650* | 0.444 | 1.037 | 1.843** | -1.319 | 0.120 | 3.584** |
| | (0.749) | (0.929) | (0.983) | (1.094) | (0.785) | (7.648) | (0.529) | (1.796) |
| Institution index | 0.0290 | 0.0612 | 0.0432 | -0.0677 | 0.306** | 0.367 | 0.0653 | -0.344*** |
| | (0.0499) | (0.0805) | (0.0787) | (0.155) | (0.135) | (0.252) | (0.0687) | (0.120) |
| Log Patent | 0.417*** | -0.0950 | 0.301 | -0.463 | 0.400 | 2.316 | 0.302* | -1.422** |
| applications | (0.150) | (0.295) | (0.346) | (0.338) | (0.254) | (1.837) | (0.177) | (0.706) |
| Observations | 717 | 703 | 338 | 327 | 459 | 383 | 503 | 491 |
| Countries | 30 | 30 | 15 | 15 | 21 | 20 | 23 | 22 |
| Timespan | 1984-2009 | | 1984-2009 | | 1986-2009 | 1986-2006 | 1984-2009 | |
| E(Q) | 0.0000 | 0.0048 | 0.0000 | 0.2259 | 0.0000 | 0.0245 | 0.0000 | 0.0305 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1. Economic damages are measured by billion US dollars at 2005 level. The instruments we use in the specification (2) for quake-proof building and earthquake detection technologies include the maximum earthquake magnitude and counts of earthquakes with magnitude 6 or larger in year t to year t-25, and population in year t to year t-5. For flood control we use area-weighted precipitation in year t to year t-25 to instrument for all damage variables and l1.kstock in specification (2). For drought-resistant crop, we use the country aggregated mean SPEI value tin year t to year t-25 and population in year t to year t-5 to instrument for all damage variables and l1.kstock.

## Table 5. Regression Results in Response to Global Death and Damage

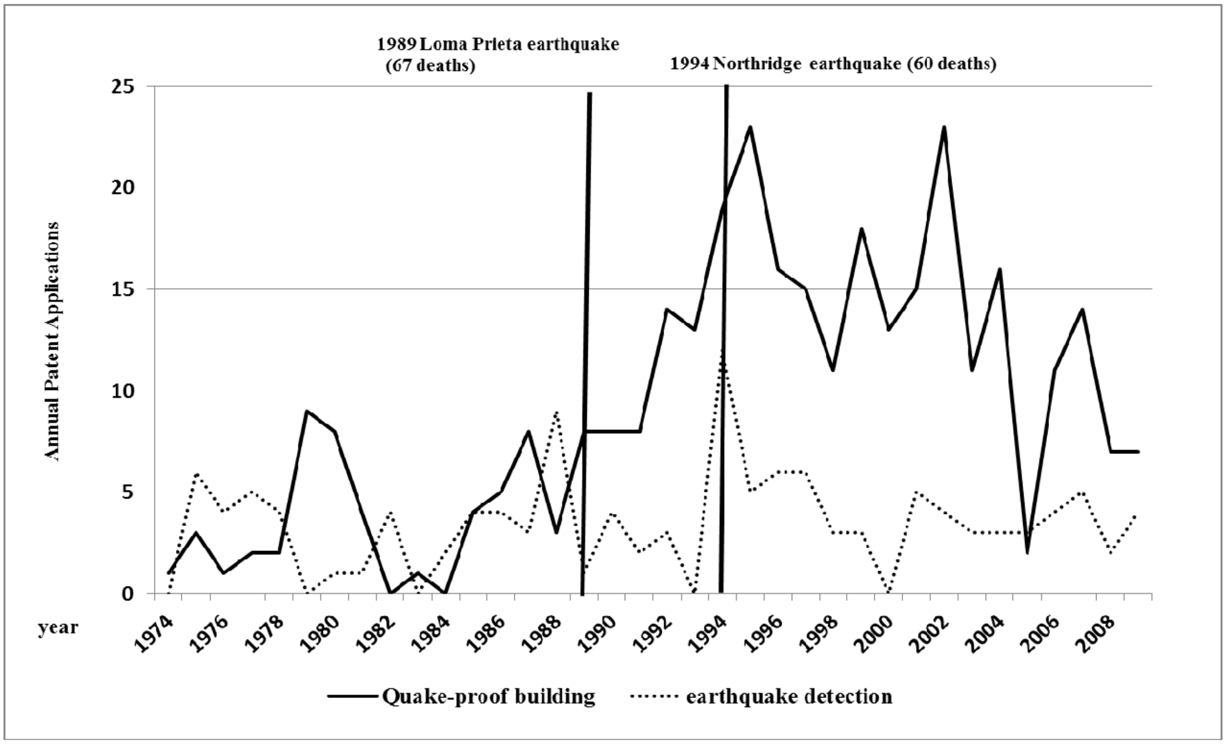
| *Technology* | *Quake-proof Building* | | *Detection* | | *Flood Control* | | *Crop* |
|---|---|---|---|---|---|---|---|
| Impact measure | Death | Damage | Death | Damage | Death | Damage | Damage |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **year 0** | 0.0187*** | 0.00408*** | 0.0167*** | 0.00928*** | 0.268*** | 0.0355** | 0.0618** |
| | (0.00497) | (0.000737) | (0.00187) | (0.000606) | (0.0841) | (0.0144) | (0.0246) |
| **year -1** | 0.0124* | 0.00355*** | 0.00944*** | 0.00264** | 0.153* | 0.0456** | 0.0488* |
| | (0.00636) | (0.000345) | (0.00337) | (0.00115) | (0.0822) | (0.0183) | (0.0276) |
| **year -2** | 0.0404*** | 0.00386*** | 0.0427* | 0.00352*** | 0.301*** | 0.0356*** | 0.0845*** |
| | (0.0111) | (0.000616) | (0.0257) | (0.00120) | (0.0586) | (0.0124) | (0.0248) |
| **year -3** | 0.0283** | 0.00495*** | 0.0199 | 0.00234** | 0.174** | 0.0136 | 0.0320*** |
| | (0.0142) | (0.000709) | (0.0226) | (0.00103) | (0.0714) | (0.0121) | (0.00661) |
| **year -4** | 0.0378*** | 0.00445*** | 0.00226 | -0.000272 | 0.0766* | 0.0289*** | 0.0352*** |
| | (0.00504) | (0.000584) | (0.0146) | (0.00115) | (0.0458) | (0.00924) | (0.0100) |
| **year -5** | 0.0103* | 0.00249*** | -0.0562** | -0.000564 | 0.0999 | 0.0229*** | 0.0509*** |
| | (0.00580) | (0.000461) | (0.0226) | (0.000679) | (0.0745) | (0.00418) | (0.00779) |
| **sum of domestic shocks** | 0.148*** | 0.023*** | 0.035 | 0.017*** | 1.072*** | 0.182*** | 0.313*** |
| | (0.0292) | (0.0010) | (0.0515) | (0.0044) | (0.2817) | (0.0680) | (0.0772) |
| **year 0** | -0.00152 | -0.000500 | 0.000733*** | 0.00156* | 0.0185*** | -0.0135*** | 0.0102 |
| | (0.00113) | (0.000903) | (0.000249) | (0.000857) | (0.00355) | (0.00505) | (0.0107) |
| **year -1** | -0.00308*** | -0.000916 | -0.000373 | -0.00270 | 0.00779 | 0.00469 | 0.0264* |
| | (0.00104) | (0.000920) | (0.000626) | (0.00181) | (0.00638) | (0.00456) | (0.0151) |
| **year -2** | -0.00544*** | 0.00147* | -0.000350 | 0.00294** | 0.0163** | 0.000795 | 0.0342*** |
| | (0.00151) | (0.000829) | (0.000921) | (0.00150) | (0.00719) | (0.00433) | (0.0127) |
| **year -3** | -0.00707*** | -0.0000487 | 0.0000358 | 0.00213 | 0.0256*** | 0.00144 | 0.0130 |
| | (0.00196) | (0.000793) | (0.000997) | (0.00271) | (0.00642) | (0.00329) | (0.00995) |
| **year -4** | -0.00737*** | -0.00201 | -0.000563 | -0.0000288 | 0.0265*** | 0.0201*** | 0.00475 |
| | (0.00267) | (0.00209) | (0.000552) | (0.00180) | (0.00743) | (0.00318) | (0.0122) |
| **year -5** | -0.000580 | -0.00204 | -0.00219*** | 0.00386** | 0.0258*** | 0.0145*** | -0.00419 |
| | (0.000981) | (0.00143) | (0.000612) | (0.00169) | (0.00469) | (0.00489) | (0.00995) |
| **sum of foreign shocks** | -0.0251*** | -0.0040 | -0.0027 | 0.0078 | 0.1204*** | 0.0281*** | 0.0845 |
| | (0.0045) | (0.0044) | (0.0018) | (0.0074) | (0.0155) | (0.0041) | (0.0496) |
| **l6. log domestic stock** | 0.0856 | 0.0449 | -0.242 | -0.173 | 0.271*** | 0.168** | 0.247** |
| | (0.114) | (0.0663) | (0.163) | (0.205) | (0.0763) | (0.0690) | (0.107) |
| **l6. log foreign stock** | 0.102 | -0.0491 | 0.552*** | 0.604*** | -0.00977 | -0.0148 | 0.887*** |
| | (0.230) | (0.144) | (0.127) | (0.175) | (0.124) | (0.133) | (0.162) |
| **log GDP per capita** | 2.043** | 1.245*** | 1.538 | 0.863 | 1.803** | 1.702** | 0.122 |
| | (0.901) | (0.301) | (1.174) | (0.808) | (0.809) | (0.829) | (0.556) |
| **Institution index** | -0.0343 | 0.0576 | -0.0491 | 0.0345 | 0.313** | 0.335*** | 0.0377 |
| | (0.0711) | (0.0562) | (0.0897) | (0.0690) | (0.124) | (0.126) | (0.0502) |
| **log Patent applications** | 0.214 | 0.555** | 0.00944 | 0.288 | 0.317 | 0.442 | 0.227 |
| | (0.298) | (0.228) | (0.362) | (0.322) | (0.266) | (0.275) | (0.217) |
| **Observations** | 717 | 717 | 338 | 338 | 459 | 459 | 503 |
| **Countries** | 30 | 30 | 15 | 15 | 21 | 21 | 23 |

**Table 6- Regression Results in Response to Foreign Shocks (based on the same continent)**

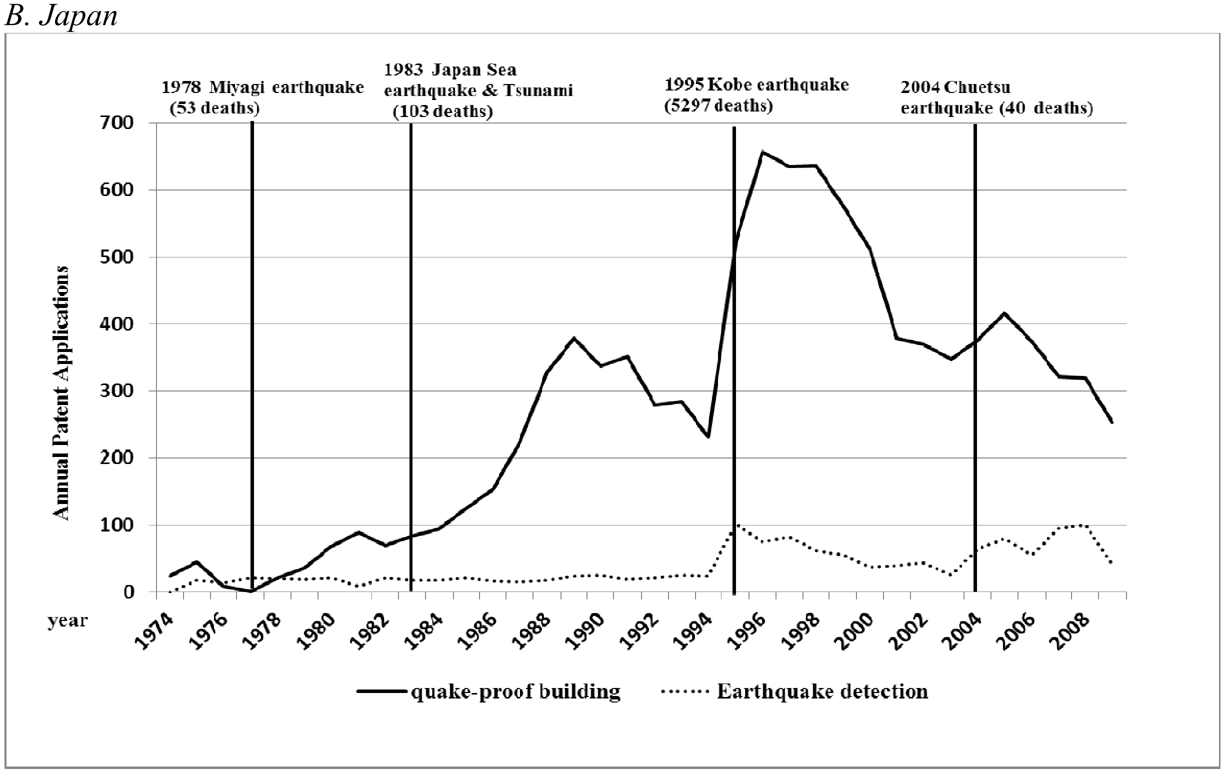
| *Technology* | *Quake-proof Building* | | *Detection* | | *Flood Control* | | *Crop* |
|---|---|---|---|---|---|---|---|
| Impact measure | Death | Damage | Death | Damage | Death | Damage | Damage |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **year 0** | 0.0190*** | 0.00273 | 0.0124*** | 0.0141*** | 0.206** | 0.0443*** | 0.0621*** |
| | (0.00697) | (0.00249) | (0.00194) | (0.00214) | (0.100) | (0.0107) | (0.00954) |
| **year -1** | 0.0106 | 0.00292 | 0.00920*** | 0.00699*** | 0.127* | 0.0532*** | 0.0105 |
| | (0.00720) | (0.00211) | (0.00229) | (0.00203) | (0.0733) | (0.0147) | (0.0209) |
| **year -2** | 0.0303* | 0.00158 | -0.00187 | 0.00330* | 0.359*** | 0.0417*** | 0.0435** |
| | (0.0165) | (0.00195) | (0.0196) | (0.00198) | (0.0890) | (0.0125) | (0.0192) |
| **year -3** | 0.0149 | 0.00422*** | -0.0103 | -0.00136 | 0.110 | 0.0126 | 0.00748 |
| | (0.0204) | (0.00153) | (0.0217) | (0.00359) | (0.0864) | (0.0121) | (0.0122) |
| **year -4** | 0.0279 | 0.00284 | -0.0282 | -0.000618 | -0.0180 | 0.0126 | 0.0213*** |
| | (0.0369) | (0.00194) | (0.0606) | (0.00236) | (0.0542) | (0.00847) | (0.00774) |
| **year -5** | 0.0685*** | 0.00240** | -0.0922 | -0.00149 | 0.122* | 0.0113* | 0.0318** |
| | (0.0204) | (0.000985) | (0.0663) | (0.00375) | (0.0704) | (0.00672) | (0.0142) |
| **sum of domestic shocks** | 0.171** | 0.017* | -0.111 | 0.021* | 0.906*** | 0.176*** | 0.177*** |
| | (0.0671) | (0.0088) | (0.1337) | (0.0122) | (0.2632) | (0.0557) | (0.0628) |
| | | | | | | | |
| **year 0** | 0.00399 | -0.00358 | 0.00192 | 0.00762*** | -0.0291 | 0.00150 | 0.000723 |
| | (0.00443) | (0.00235) | (0.00140) | (0.00179) | (0.0436) | (0.00536) | (0.0391) |
| **year -1** | 0.00244 | 0.0000405 | 0.00277** | 0.00355* | 0.0653** | 0.0212*** | -0.0183 |
| | (0.00318) | (0.00153) | (0.00130) | (0.00191) | (0.0256) | (0.00549) | (0.0257) |
| **year -2** | -0.00517* | -0.00484 | 0.00414*** | -0.000691 | 0.110* | 0.0120** | -0.0422 |
| | (0.00294) | (0.00350) | (0.00129) | (0.00158) | (0.0568) | (0.00608) | (0.0463) |
| **year -3** | -0.00141 | -0.000453 | 0.00197 | -0.00454* | -0.0245 | 0.000726 | -0.00301 |
| | (0.00253) | (0.00224) | (0.00200) | (0.00271) | (0.0662) | (0.00654) | (0.0167) |
| **year -4** | -0.00239 | -0.000591 | 0.00486*** | -0.000917 | -0.0157 | -0.00413 | -0.0198 |
| | (0.00265) | (0.00153) | (0.000846) | (0.00145) | (0.0352) | (0.00571) | (0.0215) |
| **year -5** | -0.00749** | -0.000887 | 0.00416 | 0.00256 | 0.00922 | 0.00324 | -0.00398 |
| | (0.00300) | (0.00307) | (0.00292) | (0.00333) | (0.0292) | (0.00632) | (0.0201) |
| **sum of foreign shocks** | -0.0100 | -0.0103 | 0.0198*** | 0.0076 | 0.1154 | 0.0345** | -0.0865 |
| | (0.0095) | (0.0080) | (0.0041) | (0.0067) | (0.1076) | (0.0152) | 0.0762 |
| | | | | | | | |
| **l6. log domestic stock** | 0.294 | 0.226 | -0.480*** | -0.159 | 0.247*** | 0.112 | 0.0102 |
| | (0.255) | (0.224) | (0.115) | (0.225) | (0.0942) | (0.0764) | (0.116) |
| **log GDP per capita** | 1.964* | 1.648** | 1.963*** | 0.659 | 1.578* | 1.755** | 0.136 |
| | (1.017) | (0.738) | (0.673) | (0.847) | (0.837) | (0.718) | (0.510) |
| **Institution Index** | 0.0110 | 0.0244 | 0.0762 | 0.0437 | 0.294** | 0.315** | 0.0686 |
| | (0.0609) | (0.0468) | (0.0887) | (0.0672) | (0.144) | (0.148) | (0.0713) |
| **log Patent Applications** | 0.286* | 0.395*** | -0.0106 | 0.268 | 0.328 | 0.467* | 0.270 |
| | (0.169) | (0.138) | (0.237) | (0.280) | (0.262) | (0.243) | (0.185) |
| | | | | | | | |
| **Observations** | 717 | 717 | 338 | 338 | 459 | 459 | 503 |
| **Countries** | 30 | 30 | 15 | 15 | 21 | 21 | 23 |

**Figure 1: Patenting of earthquake-mitigation technology**

*A. United States*

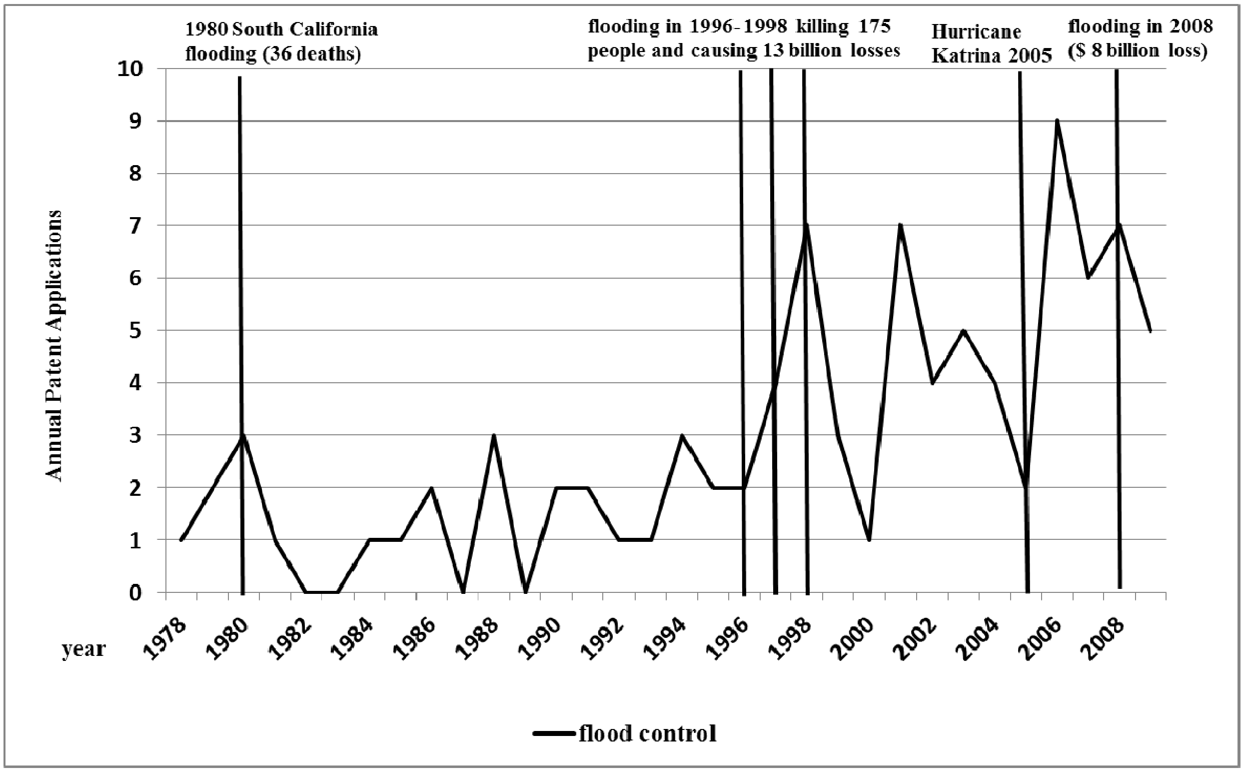



*B. Japan*



## Figure 2: Patenting of flood control technology

*A. United States*




*B. United Kingdom*

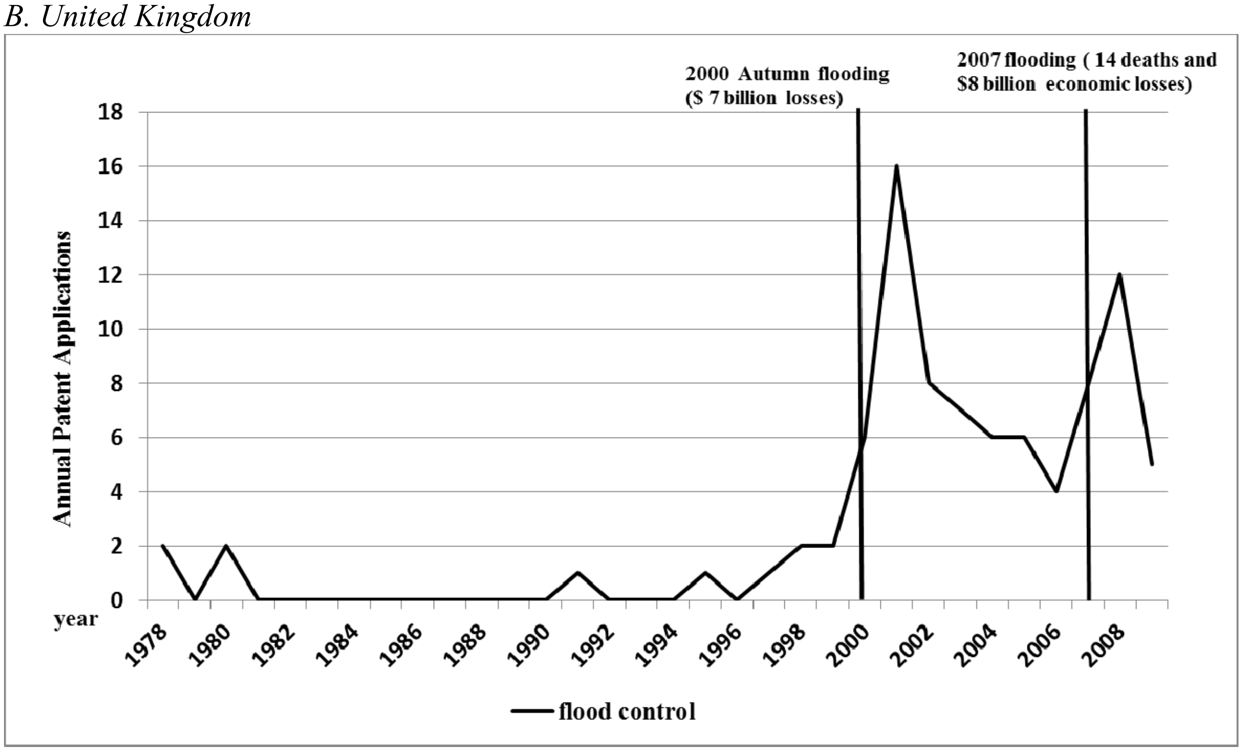
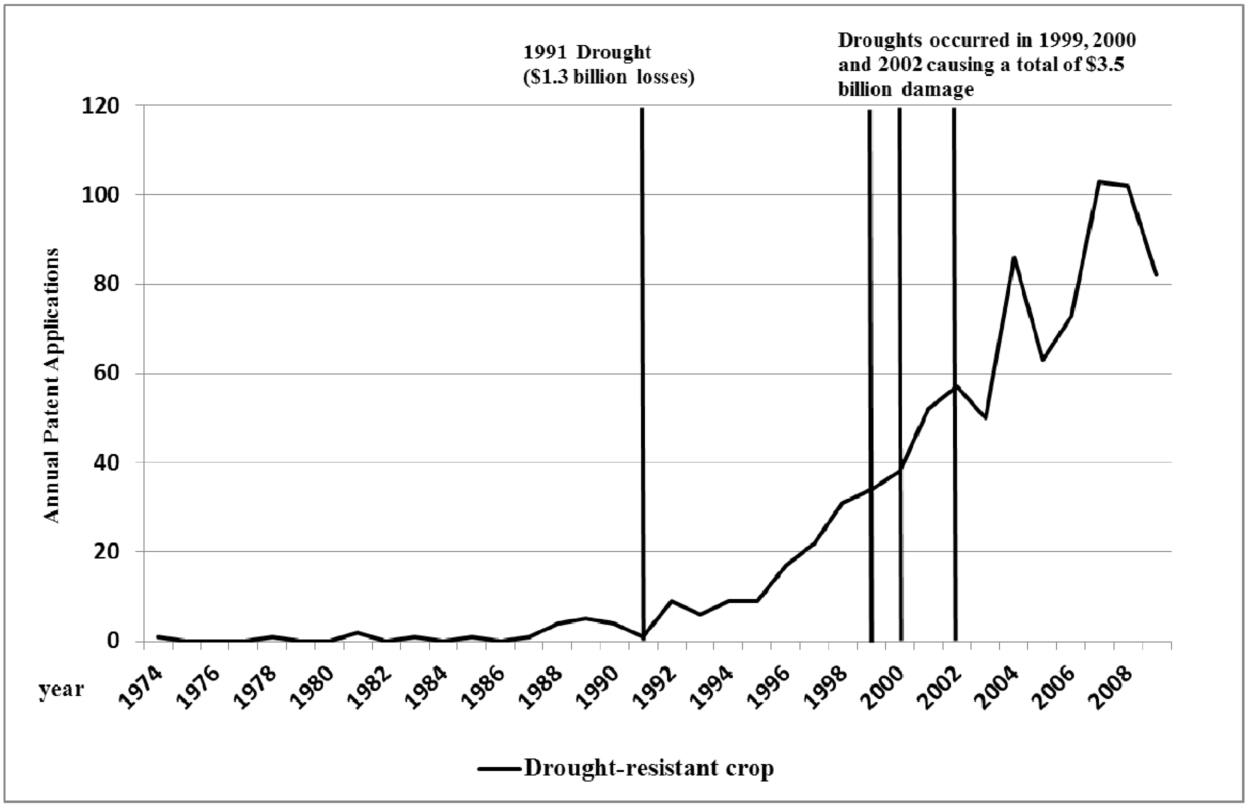
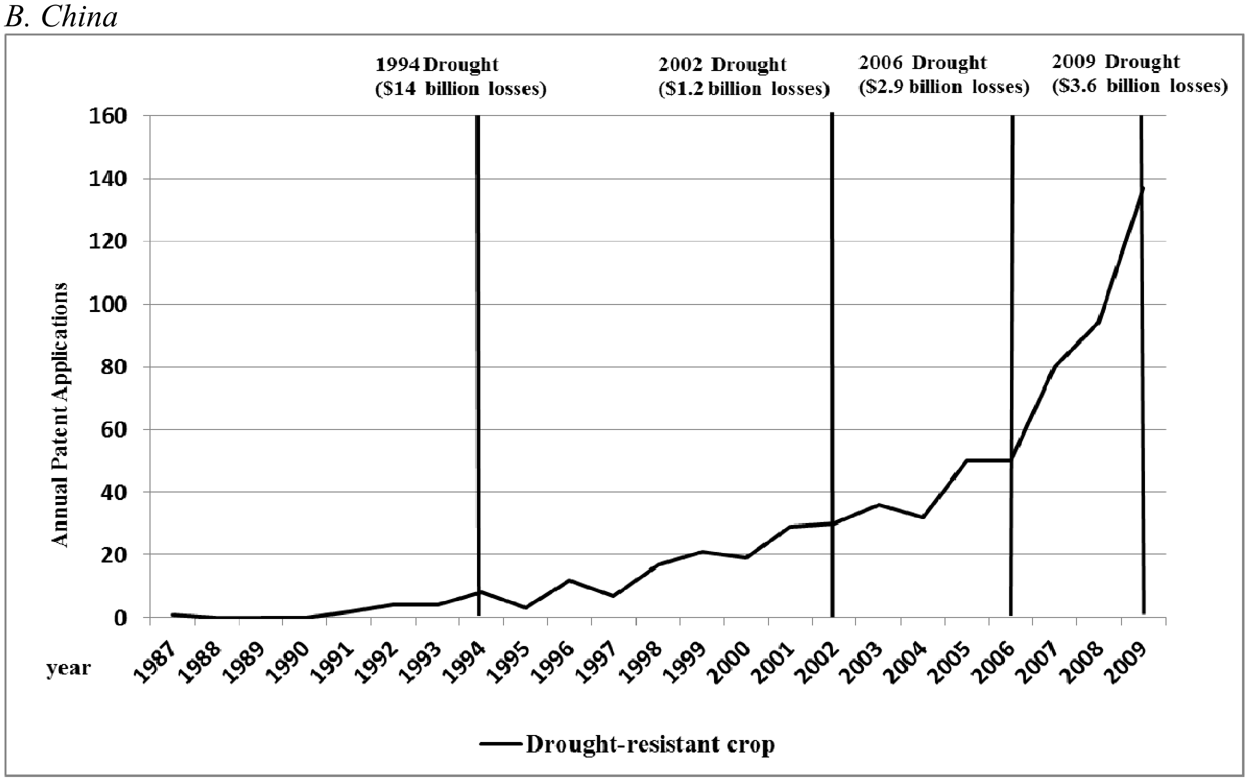


**Figure 3: Patenting of drought-resistant crop technology**

*A. United States*




*B. China*



## Appendix 1. Patent Search Codes

**Earthquake–proof building**
((E04H 00902) <in> IC)

**Earthquake detection**
((G08B 02110 OR G01V OR G01H) <in> IC) AND (earthquake <in> (TI, AB))

**Drought-resistant crops**
((drought AND (tolerant OR tolerance OR resistant OR resisting OR resistance OR combat OR fight)) <in> (AB, TI))

**Desalination**
((C02F 10308 <in> IC) AND ((desalination OR desalinization OR desalinating) <in> (TI, AB))) OR (((desalination OR desalinization OR desalinating) AND (((sea OR ocean) AND water) OR seawater)) <in> (TI, AB))

**Flood control**
(flood <in> (AB,TI)) AND ((E02B 0030? OR E02B 0031? OR E02B 007??) <in> IC)

**Appendix 2. Sample Countries for each type of technology**

- Quake-proof Building

Argentina
Australia
Austria
Belarus
Belgium
Bulgaria
Canada
China
Denmark
France
Former Soviet Union
Germany
Greece
Hungary
Italy
Japan
Mexico
Netherlands
New Zealand
Poland
Republic of Korea
Romania
Russia
Spain
Sweden
Switzerland
Taiwan
Ukraine
United Kingdom
United States

- Earthquake Detection

Canada
China
France
Former Soviet Union
Germany
Greece
Israel
Italy
Japan
Republic of Korea
Russia
Taiwan
Ukraine
United Kingdom
United States

- Drought-resistant Crop

Australia
Austria
Belgium
Brazil
Canada
China
East Germany
France
Former Soviet Union
Germany
Hungary
India
Israel
Japan
Mexico
Netherlands
New Zealand
Republic of Korea
Russia
Spain
Switzerland
United Kingdom
United States

- Flood Control

Australia
Austria
Canada
China
Czech Republic
France
Former Soviet Union
Germany
Hungary
Italy
Japan
Netherlands
Poland
Republic of Korea
Romania
Russia
Sweden
Switzerland
Taiwan
United Kingdom
United States

## Appendix 3. Sensitivity to Lag Length

In the main paper, we include deaths and damages lagged through year 5. In this appendix we demonstrate that our results are robust to different lag lengths. The tables in this section present reduced form estimates (corresponding to column (1) in Tables 3 and 4) including lags from 3 to 8 years. The results are not sensitive to the length of the lag. In particular, there is little change in the magnitude of coefficients for recent years as more distant lags are added to the model. Moreover, with the exception of flood control in reaction to deaths, the sum of all damage or death coefficients experience little change when adding more than five years of lags.

We choose to present lags of five years in the paper as nearly all lagged values are insignificant after 5 years. Moreover, the AIC statistics verify that either a four or five year lag is optimal for all technologies except drought-resistant crops. Thus, for ease of presentation in the main text, we choose a lag of five years for all technologies.

**Table A1: Lag sensitivity: Deaths as Independent Variable**

*A. Quake-proof buildings*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.0155*** | 0.0152*** | 0.0149*** | 0.0145** | 0.0141** | 0.0139* |
| | (0.00513) | (0.00542) | (0.00540) | (0.00578) | (0.00654) | (0.00750) |
| year -1 | 0.00807 | 0.00853 | 0.00821 | 0.00810 | 0.00766 | 0.00761 |
| | (0.00634) | (0.00621) | (0.00653) | (0.00685) | (0.00775) | (0.00892) |
| year -2 | 0.0256** | 0.0260** | 0.0242* | 0.0222 | 0.0228 | 0.0251 |
| | (0.0117) | (0.0118) | (0.0130) | (0.0144) | (0.0153) | (0.0154) |
| year -3 | 0.0135 | 0.0127 | 0.0123 | 0.0107 | 0.0132 | 0.0177 |
| | (0.0182) | (0.0182) | (0.0183) | (0.0186) | (0.0181) | (0.0171) |
| year -4 | | 0.0504 | 0.0471 | 0.0385 | 0.0358 | 0.0444 |
| | | (0.0332) | (0.0336) | (0.0370) | (0.0403) | (0.0366) |
| year -5 | | | 0.0800*** | 0.0683*** | 0.0662*** | 0.0718*** |
| | | | (0.0209) | (0.0221) | (0.0257) | (0.0278) |
| year -6 | | | | -0.0384 | -0.0447 | -0.0409 |
| | | | | (0.0321) | (0.0356) | (0.0385) |
| year -7 | | | | | -0.0130 | -0.0143 |
| | | | | | (0.0287) | (0.0289) |
| year -8 | | | | | | -0.0121 |
| | | | | | | (0.0386) |
| sum of shocks | 0.063* | 0.113** | 0.187*** | 0.124 | 0.102 | 0.113 |
| | (0.0346) | (0.0513) | (0.0561) | (0.0905) | (0.1135) | (0.1220) |
| L4.log stock | 0.312 | | | | | |
| | (0.227) | | | | | |
| L5.log stock | | 0.284 | | | | |
| | | (0.226) | | | | |
| L6.log stock | | | 0.265 | | | |
| | | | (0.224) | | | |
| L7.log stock | | | | 0.256 | | |
| | | | | (0.230) | | |
| L8.log stock | | | | | 0.196 | |
| | | | | | (0.235) | |
| L9.log stock | | | | | | 0.0973 |
| | | | | | | (0.228) |
| log GDP per capita | 1.834* | 1.862* | 1.904* | 1.960* | 1.930 | 1.823 |
| | (0.989) | (1.026) | (1.056) | (1.145) | (1.234) | (1.315) |
| Institution Index | -0.000254 | 0.00307 | 0.00817 | 0.0107 | 0.00650 | -0.00272 |
| | (0.0528) | (0.0564) | (0.0622) | (0.0657) | (0.0689) | (0.0688) |
| log Patent apps | 0.298* | 0.313* | 0.317* | 0.333* | 0.375** | 0.416** |
| | (0.179) | (0.176) | (0.179) | (0.183) | (0.187) | (0.192) |
| AIC | 2247.92 | 2249.90 | 2244.42 | 2247.16 | 2266.31 | 2284.29 |
| Observations | 717 | 717 | 717 | 717 | 717 | 717 |
| Countries | 30 | 30 | 30 | 30 | 30 | 30 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

*B. Earthquake Detection*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.0134*** | 0.0131*** | 0.0130*** | 0.0133*** | 0.0137*** | 0.0142*** |
| | (0.00206) | (0.00212) | (0.00224) | (0.00223) | (0.00228) | (0.00232) |
| year -1 | 0.0103*** | 0.00988*** | 0.00951*** | 0.00969*** | 0.0105*** | 0.0113*** |
| | (0.00197) | (0.00212) | (0.00248) | (0.00263) | (0.00257) | (0.00243) |
| year -2 | -0.00283 | -0.00323 | -0.00736 | -0.00621 | -0.00638 | -0.00779 |
| | (0.0270) | (0.0232) | (0.0221) | (0.0252) | (0.0285) | (0.0291) |
| year -3 | -0.00193 | -0.00174 | -0.00297 | -0.00290 | 0.00164 | 0.000735 |
| | (0.0291) | (0.0235) | (0.0203) | (0.0215) | (0.0276) | (0.0297) |
| year -4 | | -0.0425 | -0.0546 | -0.0630 | -0.0513 | -0.0419 |
| | | (0.0499) | (0.0652) | (0.0729) | (0.0751) | (0.0686) |
| year -5 | | | -0.104 | -0.113 | -0.106 | -0.0962 |
| | | | (0.0674) | (0.0751) | (0.0814) | (0.0796) |
| year -6 | | | | -0.101*** | -0.0944** | -0.0840* |
| | | | | (0.0367) | (0.0439) | (0.0468) |
| year -7 | | | | | -0.0345 | -0.0324 |
| | | | | | (0.0450) | (0.0470) |
| year -8 | | | | | | -0.117*** |
| | | | | | | (0.0450) |
| sum of shocks | 0.019 | -0.025 | -0.147 | -0.263 | -0.267 | -0.353 |
| | (0.0519) | (0.0666) | (0.1332) | (0.1781) | (0.2304) | (0.2587) |
| L4.log stock | -0.163 | | | | | |
| | (0.130) | | | | | |
| L5.log stock | | -0.248** | | | | |
| | | (0.116) | | | | |
| L6.log stock | | | -0.262 | | | |
| | | | (0.166) | | | |
| L7.log stock | | | | -0.243 | | |
| | | | | (0.166) | | |
| L8.log stock | | | | | -0.142 | |
| | | | | | (0.179) | |
| L9.log stock | | | | | | -0.0519 |
| | | | | | | (0.176) |
| log GDP per capita | 0.372 | 0.628 | 0.622 | 0.469 | 0.113 | -0.140 |
| | (0.980) | (0.994) | (1.082) | (1.092) | (1.020) | (0.982) |
| Institution Index | 0.101 | 0.0933 | 0.0941 | 0.0931 | 0.102 | 0.115 |
| | (0.116) | (0.106) | (0.110) | (0.120) | (0.130) | (0.131) |
| log Patent apps | 0.347 | 0.315 | 0.343 | 0.396 | 0.459 | 0.482 |
| | (0.369) | (0.384) | (0.413) | (0.432) | (0.438) | (0.457) |
| AIC | 1072.24 | 1067.99 | 1065.88 | 1066.52 | 1074.86 | 1074.12 |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| Countries | 15 | 15 | 15 | 15 | 15 | 15 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

*C. Flood control*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.190** | 0.184** | 0.214** | 0.273** | 0.257* | 0.272* |
| | (0.0787) | (0.0807) | (0.0986) | (0.126) | (0.131) | (0.142) |
| year -1 | 0.113** | 0.105** | 0.131** | 0.171** | 0.210** | 0.198** |
| | (0.0535) | (0.0535) | (0.0620) | (0.0735) | (0.0845) | (0.0796) |
| year -2 | 0.310*** | 0.301*** | 0.312*** | 0.344*** | 0.368*** | 0.360*** |
| | (0.0928) | (0.101) | (0.0968) | (0.0906) | (0.0945) | (0.0932) |
| year -3 | 0.167*** | 0.154** | 0.120* | 0.146** | 0.178*** | 0.182*** |
| | (0.0636) | (0.0632) | (0.0650) | (0.0651) | (0.0629) | (0.0675) |
| year -4 | | 0.0212 | 0.0107 | -0.0259 | -0.0180 | -0.0132 |
| | | (0.0415) | (0.0434) | (0.0361) | (0.0354) | (0.0401) |
| year -5 | | | 0.0958 | 0.0977 | 0.0479 | 0.0447 |
| | | | (0.0706) | (0.0772) | (0.0643) | (0.0627) |
| year -6 | | | | 0.141** | 0.146* | 0.123** |
| | | | | (0.0680) | (0.0745) | (0.0621) |
| year -7 | | | | | 0.121*** | 0.104* |
| | | | | | (0.0460) | (0.0563) |
| year -8 | | | | | | 0.0262 |
| | | | | | | (0.0462) |
| sum of shocks | 0.780*** | 0.765*** | 0.884*** | 1.146*** | 1.309*** | 1.297*** |
| | (0.1904) | (0.1700) | (0.2339) | (0.3644) | (0.4249) | (0.4514) |
| L4.log stock | 0.238** | | | | | |
| | (0.112) | | | | | |
| L5.log stock | | 0.303*** | | | | |
| | | (0.0894) | | | | |
| L6.log stock | | | 0.254*** | | | |
| | | | (0.0891) | | | |
| L7.log stock | | | | 0.177 | | |
| | | | | (0.139) | | |
| L8.log stock | | | | | 0.106 | |
| | | | | | (0.173) | |
| L9.log stock | | | | | | -0.0827 |
| | | | | | | (0.163) |
| log GDP per capita | 1.600** | 1.659** | 1.845** | 2.045** | 2.086** | 2.060** |
| | (0.683) | (0.737) | (0.825) | (0.892) | (0.921) | (0.964) |
| Institution Index | 0.285** | 0.293** | 0.297** | 0.288** | 0.282** | 0.273** |
| | (0.126) | (0.129) | (0.135) | (0.130) | (0.128) | (0.124) |
| log Patent apps | 0.331 | 0.269 | 0.286 | 0.366 | 0.439 | 0.543* |
| | (0.270) | (0.247) | (0.250) | (0.277) | (0.293) | (0.285) |
| AIC | 1321.00 | 1314.21 | 1322.01 | 1328.27 | 1332.17 | 1334.88 |
| Observations | 459 | 459 | 459 | 459 | 459 | 459 |
| Countries | 21 | 21 | 21 | 21 | 21 | 21 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

**Table A2: Lag sensitivity: Damages as Independent Variable**
*A. Quake-proof buildings*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.00411 | 0.00417 | 0.00443 | 0.00435 | 0.00456 | 0.00473 |
| | (0.00384) | (0.00377) | (0.00380) | (0.00385) | (0.00373) | (0.00357) |
| year -1 | 0.00275 | 0.00293 | 0.00322 | 0.00315 | 0.00335* | 0.00374** |
| | (0.00172) | (0.00190) | (0.00196) | (0.00206) | (0.00202) | (0.00175) |
| year -2 | 0.00268** | 0.00274** | 0.00286** | 0.00282* | 0.00306** | 0.00354** |
| | (0.00120) | (0.00130) | (0.00144) | (0.00147) | (0.00144) | (0.00140) |
| year -3 | 0.0044*** | 0.0046*** | 0.0047*** | 0.00450*** | 0.00478*** | 0.00524*** |
| | (0.00066) | (0.00088) | (0.0010) | (0.00124) | (0.00112) | (0.000890) |
| year -4 | | 0.00248* | 0.00280** | 0.00257* | 0.00264 | 0.00313** |
| | | (0.00126) | (0.00133) | (0.00154) | (0.00165) | (0.00149) |
| year -5 | | | 0.0030*** | 0.00268** | 0.00276** | 0.00315** |
| | | | (0.00101) | (0.00123) | (0.00136) | (0.00140) |
| year -6 | | | | -0.000446 | -0.000429 | -0.000108 |
| | | | | (0.00137) | (0.00154) | (0.00154) |
| year -7 | | | | | 0.000493 | 0.000771 |
| | | | | | (0.00122) | (0.00126) |
| year -8 | | | | | | 0.00118 |
| | | | | | | (0.00138) |
| sum of shocks | 0.014** | 0.017** | 0.021** | 0.020* | 0.021* | 0.025** |
| | (0.0058) | (0.0071) | (0.0081) | (0.0100) | (0.0112) | (0.0114) |
| L4.log stock | 0.263 | | | | | |
| | (0.213) | | | | | |
| L5.log stock | | 0.226 | | | | |
| | | (0.221) | | | | |
| L6.log stock | | | 0.195 | | | |
| | | | (0.222) | | | |
| L7.log stock | | | | 0.189 | | |
| | | | | (0.226) | | |
| L8.log stock | | | | | 0.140 | |
| | | | | | (0.217) | |
| L9.log stock | | | | | | 0.0570 |
| | | | | | | (0.177) |
| log GDP per capita | 1.786*** | 1.764** | 1.710** | 1.753** | 1.683** | 1.551* |
| | (0.687) | (0.724) | (0.749) | (0.837) | (0.852) | (0.802) |
| Institution Index | 0.0246 | 0.0266 | 0.0290 | 0.0290 | 0.0265 | 0.0222 |
| | (0.0426) | (0.0458) | (0.0499) | (0.0507) | (0.0512) | (0.0490) |
| log Patent apps | 0.389** | 0.408*** | 0.417*** | 0.427*** | 0.452*** | 0.473*** |
| | (0.156) | (0.151) | (0.150) | (0.156) | (0.165) | (0.178) |
| AIC | 2279.89 | 2278.66 | 2272.21 | 2275.11 | 2285.71 | 2294.07 |
| Observations | 717 | 717 | 717 | 717 | 717 | 717 |
| Countries | 30 | 30 | 30 | 30 | 30 | 30 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

*B. Earthquake Detection*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.0093*** | 0.0090*** | 0.0085*** | 0.0085*** | 0.0088*** | 0.0089*** |
| | (0.00129) | (0.00144) | (0.00189) | (0.00182) | (0.00167) | (0.00153) |
| year -1 | 0.0058*** | 0.0052*** | 0.0046*** | 0.0045** | 0.0049*** | 0.0049*** |
| | (0.00137) | (0.00153) | (0.00172) | (0.00175) | (0.00168) | (0.00141) |
| year -2 | 0.00497** | 0.00443** | 0.00358* | 0.00356** | 0.00403** | 0.00383** |
| | (0.00195) | (0.00204) | (0.00198) | (0.00178) | (0.00180) | (0.00157) |
| year -3 | 0.00198 | 0.00164 | 0.000752 | 0.000609 | 0.00120 | 0.00102 |
| | (0.00315) | (0.00306) | (0.00318) | (0.00321) | (0.00318) | (0.00296) |
| year -4 | | 0.00157 | 0.000666 | 0.000354 | 0.000895 | 0.000740 |
| | | (0.00181) | (0.00230) | (0.00255) | (0.00246) | (0.00216) |
| year -5 | | | -0.00295 | -0.00330 | -0.00289 | -0.00310 |
| | | | (0.00227) | (0.00245) | (0.00269) | (0.00247) |
| year -6 | | | | -0.00223 | -0.00187 | -0.00215 |
| | | | | (0.00162) | (0.00187) | (0.00174) |
| year -7 | | | | | -0.000470 | -0.000886 |
| | | | | | (0.00209) | (0.00197) |
| year -8 | | | | | | -0.00301* |
| | | | | | | (0.00169) |
| sum of shocks | 0.022*** | 0.022*** | 0.015 | 0.012 | 0.015 | 0.010 |
| | (0.0060) | (0.0078) | (0.0115) | (0.0131) | (0.0147) | (0.0143) |
| L4.log stock | 0.0921 | | | | | |
| | (0.213) | | | | | |
| L5.log stock | | -0.0305 | | | | |
| | | (0.202) | | | | |
| L6.log stock | | | -0.129 | | | |
| | | | (0.245) | | | |
| L7.log stock | | | | -0.134 | | |
| | | | | (0.231) | | |
| L8.log stock | | | | | -0.0555 | |
| | | | | | (0.221) | |
| L9.log stock | | | | | | -0.0693 |
| | | | | | | (0.213) |
| log GDP per capita | -0.170 | 0.177 | 0.444 | 0.425 | 0.192 | 0.182 |
| | (0.904) | (0.928) | (0.983) | (0.928) | (0.846) | (0.826) |
| Institution Index | 0.0487 | 0.0481 | 0.0432 | 0.0389 | 0.0415 | 0.0395 |
| | (0.0910) | (0.0850) | (0.0787) | (0.0785) | (0.0815) | (0.0784) |
| log Patent apps | 0.357 | 0.309 | 0.301 | 0.322 | 0.343 | 0.357 |
| | (0.319) | (0.332) | (0.346) | (0.352) | (0.349) | (0.372) |
| AIC | 1054.58 | 1056.02 | 1053.58 | 1054.19 | 1057.99 | 1056.78 |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| Countries | 15 | 15 | 15 | 15 | 15 | 15 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

*C. Flood Control*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.0470*** | 0.0456*** | 0.0476*** | 0.0542*** | 0.0549*** | 0.0541*** |
| | (0.0134) | (0.0125) | (0.0123) | (0.0127) | (0.0133) | (0.0128) |
| year -1 | 0.0407** | 0.0416*** | 0.0414*** | 0.0429*** | 0.0419** | 0.0420** |
| | (0.0159) | (0.0160) | (0.0157) | (0.0163) | (0.0165) | (0.0164) |
| year -2 | 0.0324*** | 0.0314*** | 0.0323*** | 0.0349*** | 0.0365*** | 0.0350*** |
| | (0.00911) | (0.00949) | (0.00954) | (0.00957) | (0.00984) | (0.0115) |
| year -3 | 0.0115 | 0.0115 | 0.0111 | 0.0163 | 0.0156* | 0.0178* |
| | (0.00819) | (0.00933) | (0.00948) | (0.0101) | (0.00831) | (0.0101) |
| year -4 | | 0.0128* | 0.0121* | 0.0135* | 0.0125** | 0.0129** |
| | | (0.00668) | (0.00681) | (0.00713) | (0.00620) | (0.00636) |
| year -5 | | | 0.00492 | 0.00588 | 0.00591 | 0.00502 |
| | | | (0.00497) | (0.00486) | (0.00436) | (0.00527) |
| year -6 | | | | 0.0118** | 0.0109** | 0.0109** |
| | | | | (0.00524) | (0.00508) | (0.00502) |
| year -7 | | | | | -0.00568 | -0.00664 |
| | | | | | (0.00648) | (0.00628) |
| year -8 | | | | | | -0.00689 |
| | | | | | | (0.00576) |
| sum of shocks | 0.132*** | 0.143*** | 0.149*** | 0.180*** | 0.172*** | 0.164*** |
| | (0.0430) | (0.0500) | (0.0530) | (0.0553) | (0.0516) | (0.0566) |
| L4.log stock | 0.195** | | | | | |
| | (0.0927) | | | | | |
| L5.log stock | | 0.212** | | | | |
| | | (0.0903) | | | | |
| L6.log stock | | | 0.146* | | | |
| | | | (0.0768) | | | |
| L7.log stock | | | | 0.0750 | | |
| | | | | (0.0941) | | |
| L8.log stock | | | | | 0.0379 | |
| | | | | | (0.127) | |
| L9.log stock | | | | | | -0.124 |
| | | | | | | (0.145) |
| log GDP per capita | 1.622** | 1.738** | 1.843** | 1.895** | 1.852** | 1.803** |
| | (0.709) | (0.729) | (0.785) | (0.820) | (0.876) | (0.916) |
| Institution Index | 0.302** | 0.306** | 0.306** | 0.303** | 0.297** | 0.286** |
| | (0.124) | (0.128) | (0.135) | (0.131) | (0.132) | (0.127) |
| log Patent apps | 0.401 | 0.382 | 0.400 | 0.482* | 0.510** | 0.611** |
| | (0.263) | (0.263) | (0.254) | (0.258) | (0.256) | (0.258) |
| AIC | 1282.88 | 1280.86 | 1288.32 | 1290.82 | 1292.92 | 1291.57 |
| Observations | 459 | 459 | 459 | 459 | 459 | 459 |
| Countries | 21 | 21 | 21 | 21 | 21 | 21 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

*D. Drought-resistant crops*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| year 0 | 0.0746*** | 0.0717*** | 0.0659*** | 0.0651*** | 0.0611*** | 0.0643*** |
| | (0.0132) | (0.0131) | (0.0140) | (0.0155) | (0.0140) | (0.0143) |
| year -1 | 0.0140 | 0.0173 | 0.0177 | 0.0159 | 0.0187 | 0.0207 |
| | (0.0219) | (0.0218) | (0.0209) | (0.0195) | (0.0198) | (0.0192) |
| year -2 | 0.0509*** | 0.0522*** | 0.0514*** | 0.0493** | 0.0508*** | 0.0593*** |
| | (0.0177) | (0.0181) | (0.0197) | (0.0192) | (0.0191) | (0.0195) |
| year -3 | 0.00350 | 0.00675 | 0.00771 | 0.00512 | 0.00541 | 0.0132 |
| | (0.0128) | (0.0125) | (0.0124) | (0.0128) | (0.0131) | (0.0132) |
| year -4 | | 0.0176** | 0.0246*** | 0.0239*** | 0.0205* | 0.0270*** |
| | | (0.00732) | (0.00806) | (0.00926) | (0.0108) | (0.0102) |
| year -5 | | | 0.0346*** | 0.0349*** | 0.0370*** | 0.0334*** |
| | | | (0.00907) | (0.00976) | (0.00958) | (0.00980) |
| year -6 | | | | -0.00338 | 0.000467 | 0.00159 |
| | | | | (0.00964) | (0.00991) | (0.0102) |
| year -7 | | | | | 0.0124 | 0.0184* |
| | | | | | (0.0103) | (0.00969) |
| year -8 | | | | | | 0.0308*** |
| | | | | | | (0.0105) |
| sum of shocks | 0.143*** | 0.166*** | 0.202*** | 0.191*** | 0.206*** | 0.269*** |
| | (0.0513) | (0.0536) | (0.0624) | (0.0633) | (0.0613) | (0.0706) |
| L4.log stock | 0.182 | | | | | |
| | (0.118) | | | | | |
| L5.log stock | | 0.128 | | | | |
| | | (0.116) | | | | |
| L6.log stock | | | -0.0181 | | | |
| | | | (0.125) | | | |
| L7.log stock | | | | -0.0599 | | |
| | | | | (0.122) | | |
| L8.log stock | | | | | -0.175 | |
| | | | | | (0.112) | |
| L9.log stock | | | | | | -0.298*** |
| | | | | | | (0.105) |
| log GDP per capita | 0.339 | 0.312 | 0.120 | 0.0512 | -0.0932 | -0.286 |
| | (0.601) | (0.583) | (0.529) | (0.538) | (0.508) | (0.494) |
| Institution Index | 0.0391 | 0.0456 | 0.0653 | 0.0707 | 0.0931 | 0.124 |
| | (0.0651) | (0.0656) | (0.0687) | (0.0701) | (0.0771) | (0.0833) |
| log Patent apps | 0.0854 | 0.127 | 0.302* | 0.348* | 0.490*** | 0.676*** |
| | (0.181) | (0.181) | (0.177) | (0.192) | (0.189) | (0.201) |
| AIC | 1273.44 | 1276.90 | 1277.14 | 1278.37 | 1274.79 | 1261.78 |
| Observations | 503 | 503 | 503 | 503 | 503 | 503 |
| Countries | 23 | 23 | 23 | 23 | 23 | 23 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1.

## Appendix 4. Lag sensitivity without knowledge stocks

In this section we provide additional sensitivity analysis showing the robustness of our results to both different finite lag structures and to potential endogeneity concerns when including knowledge stocks. To avoid these endogeneity concerns about the knowledge stock, the models presented here consider a reduced form in which the knowledge stock is replaced by the sum of previous deaths or damages. Essentially, the entire history of deaths or damages for each country is included, with the coefficient constrained to be the same after $L$ years to allow estimation of the equation. The model can be written as:

(A1) $$PAT_{jit} = \sum_{l=0}^{L} \beta_l D_{i,t-l} + \beta_H \sum_{h=L+1}^{H} D_{i,t-h} + \boldsymbol{\beta}_{\mathbf{X}} \mathbf{X}_{\mathbf{it}} + \eta_i + \phi_t + \epsilon_{it}$$

For example, if $L$ = 3, the model includes a separate damage coefficient for years 0 to $t$-3, and a single coefficient, $\beta_H$, on the sum of all damages occurring from year $t$-4 onward until 1960, the first year for which we have disaster data. We denote this as year $H$ above. $\mathbf{X_{it}}$ represents a matrix of the various control variables used.

Panels A-C in Table A3 present the results for deaths and panels A-D in Table A4 present the results for damages. The tables show that our results are robust to various lag lengths. With the exception of flood control technology, lagged deaths or damages are rarely significant after four or five years. Moreover, in most cases (the effect of damages on earthquake detection being the most notable exception), the coefficient on the sum of past events is insignificant, suggesting that additional lags are unimportant. Moreover, the sums of the various $\beta_l$ coefficients, shown at the bottom of each table, are comparable to the sums found in the regressions in Tables 3 and 4 of our paper and do not vary much across various lag specifications. For example, the sum of deaths for a 5 year lag for earthquake-proof buildings, shown in panel A of Table A4, is 0.185, compared to 0.187 in the reduced form regression in Table 3 of the paper. The largest range of the sums occurs for flood control in response to deaths, with a range from 0.621-0.857.

**Table A3: Lag sensitivity without knowledge stocks: Deaths as Independent Variable**
*A. Quake-proof buildings*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Death | 0.0146** | 0.0149** | 0.0149** | 0.0149** | 0.0149** | 0.0149** |
| | (0.0065) | (0.0065) | (0.0063) | (0.0064) | (0.0063) | (0.0063) |
| L1.death | 0.0080 | 0.0084 | 0.0090 | 0.0090 | 0.0090 | 0.0090 |
| | (0.0075) | (0.0074) | (0.0072) | (0.0072) | (0.0072) | (0.0071) |
| L2.death | 0.0281** | 0.0280** | 0.0278** | 0.0277** | 0.0277** | 0.0277** |
| | (0.0116) | (0.0114) | (0.0112) | (0.0111) | (0.0112) | (0.0111) |
| L3.death | 0.0230 | 0.0222 | 0.0199 | 0.0203 | 0.0202 | 0.0201 |
| | (0.0173) | (0.0171) | (0.0171) | (0.0170) | (0.0171) | (0.0171) |
| L4.death | | 0.0448 | 0.0429 | 0.0435 | 0.0434 | 0.0435 |
| | | (0.0339) | (0.0344) | (0.0342) | (0.0345) | (0.0343) |
| L5.death | | | 0.0702** | 0.0708** | 0.0705** | 0.0704** |
| | | | (0.0320) | (0.0316) | (0.0321) | (0.0322) |
| L6.death | | | | -0.0432 | -0.0433 | -0.0435 |
| | | | | (0.0465) | (0.0471) | (0.0479) |
| L7.death | | | | | -0.0203 | -0.0204 |
| | | | | | (0.0287) | (0.0288) |
| L8.death | | | | | | -0.0228 |
| | | | | | | (0.0437) |
| Sum of past deaths | -0.0052 | -0.0136 | -0.0285 | -0.0254 | -0.0265 | -0.0273 |
| | (0.0367) | (0.0396) | (0.0432) | (0.0438) | (0.0506) | (0.0577) |
| Log GDP per capita | 1.5944* | 1.5536* | 1.5147* | 1.5232* | 1.5226* | 1.5211* |
| | (0.9556) | (0.9299) | (0.8885) | (0.9012) | (0.8999) | (0.8962) |
| Institution index | -0.0119 | -0.0128 | -0.0154 | -0.0148 | -0.0150 | -0.0151 |
| | (0.0548) | (0.0539) | (0.0529) | (0.0527) | (0.0523) | (0.0516) |
| Log patent apps | 0.4640* | 0.4503* | 0.4159* | 0.4222* | 0.4197* | 0.4184* |
| | (0.2518) | (0.2462) | (0.2456) | (0.2422) | (0.2350) | (0.2265) |
| Observations | 717 | 717 | 717 | 717 | 717 | 717 |
| sum of deaths | 0.074** | 0.118** | 0.185*** | 0.143 | 0.122 | 0.099 |
| | (0.0310) | (0.0508) | (0.0667) | (0.1055) | (0.1286) | (0.1576) |
| AIC | 2287.497 | 2282.405 | 2268.616 | 2268.126 | 2268.068 | 2268.037 |
| BIC | 2420.174 | 2415.082 | 2401.293 | 2400.803 | 2400.745 | 2400.714 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

*B. Earthquake detection*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Death | 0.0135*** | 0.0133*** | 0.0134*** | 0.0133*** | 0.0132*** | 0.0134*** |
| | (0.0016) | (0.0017) | (0.0017) | (0.0018) | (0.0018) | (0.0018) |
| L1.death | 0.0107*** | 0.0105*** | 0.0102*** | 0.0102*** | 0.0102*** | 0.0103*** |
| | (0.0022) | (0.0023) | (0.0022) | (0.0022) | (0.0022) | (0.0022) |
| L2.death | -0.0004 | -0.0001 | 0.0002 | -0.0001 | -0.0002 | -0.0006 |
| | (0.0326) | (0.0327) | (0.0328) | (0.0327) | (0.0326) | (0.0327) |
| L3.death | 0.0063 | 0.0076 | 0.0118 | 0.0155 | 0.0168 | 0.0182 |
| | (0.0313) | (0.0316) | (0.0322) | (0.0323) | (0.0323) | (0.0330) |
| L4.death | | -0.0134 | -0.0155 | -0.0099 | -0.0087 | -0.0063 |
| | | (0.0664) | (0.0671) | (0.0683) | (0.0685) | (0.0662) |
| L5.death | | | -0.0597 | -0.0591 | -0.0554 | -0.0509 |
| | | | (0.0826) | (0.0814) | (0.0827) | (0.0808) |
| L6.death | | | | -0.0472 | -0.0464 | -0.0350 |
| | | | | (0.0476) | (0.0472) | (0.0471) |
| L7.death | | | | | 0.0183 | 0.0209 |
| | | | | | (0.0587) | (0.0568) |
| L8.death | | | | | | -0.0553 |
| | | | | | | (0.0660) |
| Sum of past deaths | 0.0107 | 0.0162 | 0.0332 | 0.0539 | 0.0635 | 0.0864 |
| | (0.0724) | (0.0755) | (0.0701) | (0.0744) | (0.0790) | (0.0777) |
| Log GDP per capita | -0.0365 | -0.0727 | -0.1526 | -0.2439 | -0.2758 | -0.2975 |
| | (1.0146) | (1.0303) | (1.0603) | (1.0542) | (1.0369) | (1.0239) |
| Institution index | 0.0971 | 0.0983 | 0.1035 | 0.1111 | 0.1139 | 0.1195 |
| | (0.1340) | (0.1345) | (0.1354) | (0.1352) | (0.1345) | (0.1330) |
| Log patent apps | 0.4215 | 0.4463 | 0.5070 | 0.5753 | 0.6003* | 0.6335* |
| | (0.3183) | (0.3378) | (0.3619) | (0.3631) | (0.3535) | (0.3553) |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| sum of deaths | 0.030 | 0.018 | -0.040 | -0.077 | -0.052 | -0.085 |
| | (0.0612) | (0.1006) | (0.1707) | (0.2135) | (0.2627) | (0.3128) |
| AIC | 1038.474 | 1038.061 | 1033.985 | 1029.137 | 1028.142 | 1019.437 |
| BIC | 1091.996 | 1091.583 | 1087.507 | 1082.660 | 1081.664 | 1072.960 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

*C. Flood Control*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Death | 0.1565** | 0.1599** | 0.1647** | 0.2057** | 0.1904** | 0.1924** |
| | (0.0679) | (0.0740) | (0.0759) | (0.0911) | (0.0846) | (0.0849) |
| L1.death | 0.0671 | 0.0676 | 0.0875** | 0.1065** | 0.1332*** | 0.1226*** |
| | (0.0483) | (0.0477) | (0.0425) | (0.0425) | (0.0429) | (0.0435) |
| L2.death | 0.2784*** | 0.2706** | 0.2758*** | 0.2997*** | 0.3126*** | 0.3190*** |
| | (0.0899) | (0.1071) | (0.1045) | (0.0932) | (0.0887) | (0.0850) |
| L3.death | 0.1404** | 0.1398** | 0.0999 | 0.1155* | 0.1408** | 0.1448** |
| | (0.0606) | (0.0608) | (0.0719) | (0.0691) | (0.0600) | (0.0582) |
| L4.death | | -0.0171 | -0.0203 | -0.0647* | -0.0658* | -0.0555 |
| | | (0.0440) | (0.0436) | (0.0383) | (0.0364) | (0.0382) |
| L5.death | | | 0.0483 | 0.0521 | -0.0035 | -0.0056 |
| | | | (0.0538) | (0.0556) | (0.0392) | (0.0391) |
| L6.death | | | | 0.0845* | 0.0925* | 0.0604 |
| | | | | (0.0450) | (0.0481) | (0.0400) |
| L7.death | | | | | 0.0570 | 0.0532 |
| | | | | | (0.0501) | (0.0475) |
| L8.death | | | | | | -0.0126 |
| | | | | | | (0.0458) |
| Sum of past deaths | -0.0341 | -0.0357 | -0.0441 | -0.0565 | -0.0658* | -0.0746* |
| | (0.0382) | (0.0395) | (0.0397) | (0.0366) | (0.0361) | (0.0403) |
| Log GDP per capita | 2.0454** | 2.0707** | 2.2210** | 2.4125** | 2.5270*** | 2.6318** |
| | (0.8835) | (0.9116) | (0.9433) | (0.9475) | (0.9598) | (1.0356) |
| Institution index | 0.2673** | 0.2670** | 0.2670** | 0.2702** | 0.2748** | 0.2771** |
| | (0.1310) | (0.1302) | (0.1282) | (0.1247) | (0.1230) | (0.1220) |
| Log patent apps | 0.4298 | 0.4366 | 0.4654 | 0.5515* | 0.5967* | 0.6216** |
| | (0.3231) | (0.3222) | (0.3179) | (0.3139) | (0.3063) | (0.2977) |
| Observations | 459 | 459 | 459 | 459 | 459 | 459 |
| sum of deaths | 0.642*** | 0.621*** | 0.656*** | 0.799*** | 0.857*** | 0.819*** |
| | (0.1534) | (0.1428) | (0.1385) | (0.1583) | (0.1626) | (0.1607) |
| AIC | 1311.618 | 1311.551 | 1309.636 | 1304.491 | 1300.780 | 1299.736 |
| BIC | 1394.199 | 1394.132 | 1392.217 | 1387.072 | 1383.361 | 1382.317 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

**Table A4: Lag sensitivity without knowledge stocks: Damages as Independent Variable**

*A. Quake-proof buildings*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Damage | 0.0050 | 0.0051 | 0.0051 | 0.0051 | 0.0051 | 0.0051 |
| | (0.0031) | (0.0031) | (0.0031) | (0.0031) | (0.0032) | (0.0031) |
| L1.damage | 0.0040*** | 0.0041*** | 0.0042*** | 0.0042*** | 0.0041*** | 0.0042*** |
| | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| L2.damage | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** | 0.0045*** |
| | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) | (0.0013) |
| L3.damage | 0.0062*** | 0.0063*** | 0.0063*** | 0.0063*** | 0.0063*** | 0.0063*** |
| | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) | (0.0010) |
| L4.damage | | 0.0041*** | 0.0043*** | 0.0043*** | 0.0043*** | 0.0043*** |
| | | (0.0015) | (0.0015) | (0.0015) | (0.0015) | (0.0015) |
| L5.damage | | | 0.0045*** | 0.0044*** | 0.0044*** | 0.0044*** |
| | | | (0.0014) | (0.0014) | (0.0014) | (0.0014) |
| L6.damage | | | | 0.0012 | 0.0012 | 0.0012 |
| | | | | (0.0017) | (0.0017) | (0.0017) |
| L7.damage | | | | | 0.0021 | 0.0021 |
| | | | | | (0.0013) | (0.0013) |
| L8.damage | | | | | | 0.0025* |
| | | | | | | (0.0015) |
| Sum of past damage | 0.0026** | 0.0023* | 0.0019 | 0.0021 | 0.0021 | 0.0020 |
| | (0.0013) | (0.0013) | (0.0014) | (0.0014) | (0.0016) | (0.0018) |
| Log GDP per capita | 1.8234*** | 1.7625*** | 1.6812*** | 1.7124*** | 1.7136** | 1.6999** |
| | (0.6563) | (0.6390) | (0.6278) | (0.6553) | (0.6687) | (0.6855) |
| Institution index | 0.0371 | 0.0352 | 0.0328 | 0.0337 | 0.0338 | 0.0333 |
| | (0.0446) | (0.0441) | (0.0437) | (0.0431) | (0.0425) | (0.0414) |
| Log patent apps | 0.5236** | 0.5193** | 0.5080** | 0.5122** | 0.5126*** | 0.5099*** |
| | (0.2099) | (0.2073) | (0.2073) | (0.2040) | (0.1990) | (0.1930) |
| Observations | 717 | 717 | 717 | 717 | 717 | 717 |
| sum of damages | 0.020*** | 0.024*** | 0.029*** | 0.030*** | 0.032*** | 0.035*** |
| | (0.0048) | (0.0059) | (0.0067) | (0.0078) | (0.0089) | (0.0099) |
| AIC | 2280.224 | 2276.314 | 2268.486 | 2267.374 | 2267.370 | 2267.043 |
| BIC | 2412.901 | 2408.991 | 2401.163 | 2400.051 | 2400.047 | 2399.721 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

*B. Earthquake detection*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Damage | 0.0094*** | 0.0094*** | 0.0093*** | 0.0093*** | 0.0093*** | 0.0094*** |
| | (0.0013) | (0.0013) | (0.0013) | (0.0014) | (0.0014) | (0.0013) |
| L1.damage | 0.0060*** | 0.0060*** | 0.0059*** | 0.0059*** | 0.0059*** | 0.0059*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| L2.damage | 0.0064*** | 0.0064*** | 0.0064*** | 0.0065*** | 0.0065*** | 0.0066*** |
| | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) |
| L3.damage | 0.0038 | 0.0038 | 0.0039 | 0.0040 | 0.0041 | 0.0042 |
| | (0.0030) | (0.0030) | (0.0029) | (0.0029) | (0.0029) | (0.0029) |
| L4.damage | | 0.0040** | 0.0039** | 0.0040*** | 0.0041*** | 0.0042*** |
| | | (0.0017) | (0.0015) | (0.0015) | (0.0016) | (0.0015) |
| L5.damage | | | 0.0005 | 0.0005 | 0.0006 | 0.0009 |
| | | | (0.0021) | (0.0020) | (0.0020) | (0.0020) |
| L6.damage | | | | 0.0018 | 0.0018 | 0.0021 |
| | | | | (0.0013) | (0.0013) | (0.0014) |
| L7.damage | | | | | 0.0036* | 0.0036 |
| | | | | | (0.0022) | (0.0023) |
| L8.damage | | | | | | 0.0019 |
| | | | | | | (0.0018) |
| Sum of past damages | 0.0039** | 0.0038* | 0.0046** | 0.0054*** | 0.0059*** | 0.0069*** |
| | (0.0018) | (0.0020) | (0.0019) | (0.0021) | (0.0022) | (0.0022) |
| Log GDP per capita | 0.4995 | 0.5001 | 0.5547 | 0.5910 | 0.6122 | 0.6730 |
| | (0.8920) | (0.8908) | (0.8307) | (0.8146) | (0.8031) | (0.7797) |
| Institution index | 0.0712 | 0.0706 | 0.0724 | 0.0764 | 0.0790 | 0.0816 |
| | (0.0978) | (0.0961) | (0.0912) | (0.0881) | (0.0869) | (0.0844) |
| Log patent apps | 0.3054 | 0.3034 | 0.3300 | 0.3594 | 0.3793 | 0.3970 |
| | (0.2947) | (0.2898) | (0.2750) | (0.2612) | (0.2552) | (0.2473) |
| Observations | 338 | 338 | 338 | 338 | 338 | 338 |
| sum of damages | 0.026*** | 0.030*** | 0.030*** | 0.032*** | 0.036*** | 0.039*** |
| | (0.0044) | (0.0056) | (0.0073) | (0.0083) | (0.0101) | (0.0116) |
| AIC | 1001.577 | 1001.566 | 993.924 | 987.937 | 985.300 | 975.806 |
| BIC | 1055.099 | 1055.089 | 1047.447 | 1041.459 | 1038.823 | 1029.329 |

Robust standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

*C. Flood control*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Damage | 0.0445*** | 0.0451*** | 0.0434*** | 0.0478*** | 0.0482*** | 0.0481*** |
| | (0.0133) | (0.0135) | (0.0137) | (0.0130) | (0.0136) | (0.0135) |
| L1.damage | 0.0377** | 0.0396** | 0.0396** | 0.0373** | 0.0367** | 0.0372** |
| | (0.0155) | (0.0158) | (0.0161) | (0.0179) | (0.0167) | (0.0167) |
| L2.damage | 0.0269*** | 0.0267*** | 0.0277*** | 0.0288** | 0.0294** | 0.0289** |
| | (0.0097) | (0.0101) | (0.0103) | (0.0117) | (0.0132) | (0.0123) |
| L3.damage | 0.0047 | 0.0053 | 0.0056 | 0.0096 | 0.0096 | 0.0103 |
| | (0.0102) | (0.0109) | (0.0109) | (0.0116) | (0.0114) | (0.0128) |
| L4.damage | | 0.0053 | 0.0050 | 0.0057 | 0.0055 | 0.0056 |
| | | (0.0081) | (0.0083) | (0.0087) | (0.0084) | (0.0083) |
| L5.damage | | | -0.0019 | -0.0012 | -0.0008 | -0.0008 |
| | | | (0.0044) | (0.0049) | (0.0057) | (0.0056) |
| L6.damage | | | | 0.0032 | 0.0034 | 0.0039 |
| | | | | (0.0059) | (0.0062) | (0.0069) |
| L7.damage | | | | | -0.0128** | -0.0123*** |
| | | | | | (0.0060) | (0.0047) |
| L8.damage | | | | | | -0.0123* |
| | | | | | | (0.0068) |
| Sum of past damages | -0.0063 | -0.0074 | -0.0086* | -0.0108** | -0.0103* | -0.0098 |
| | (0.0051) | (0.0046) | (0.0047) | (0.0047) | (0.0058) | (0.0064) |
| Log GDP per capita | 1.9448** | 2.0193** | 2.1005*** | 2.1441*** | 2.1179*** | 2.0891** |
| | (0.8288) | (0.7902) | (0.7763) | (0.7414) | (0.8093) | (0.8904) |
| Institution index | 0.2810** | 0.2809** | 0.2811** | 0.2865** | 0.2857** | 0.2851** |
| | (0.1234) | (0.1216) | (0.1203) | (0.1174) | (0.1190) | (0.1200) |
| Log patent apps | 0.5546** | 0.6057** | 0.6298** | 0.7191** | 0.7100*** | 0.7044*** |
| | (0.2778) | (0.2781) | (0.2780) | (0.2798) | (0.2669) | (0.2592) |
| Observations | 459 | 459 | 459 | 459 | 459 | 459 |
| sum of damages | 0.114*** | 0.122** | 0.119** | 0.131** | 0.119* | 0.109 |
| | (0.0437) | (0.0531) | (0.0583) | (0.0646) | (0.0648) | (0.0680) |
| AIC | 1267.923 | 1264.714 | 1263.631 | 1258.947 | 1258.818 | 1258.687 |
| BIC | 1350.504 | 1347.295 | 1346.212 | 1341.528 | 1341.399 | 1341.268 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

*D. Drought-resistant crops*

| lag: | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|
| Damage | 0.0662*** | 0.0641*** | 0.0600*** | 0.0605*** | 0.0585*** | 0.0572*** |
| | (0.0088) | (0.0092) | (0.0098) | (0.0119) | (0.0125) | (0.0121) |
| L1.damage | 0.0155 | 0.0125 | 0.0109 | 0.0111 | 0.0084 | 0.0079 |
| | (0.0251) | (0.0268) | (0.0271) | (0.0278) | (0.0285) | (0.0287) |
| L2.damage | 0.0535** | 0.0506** | 0.0447* | 0.0450* | 0.0431 | 0.0369 |
| | (0.0242) | (0.0250) | (0.0263) | (0.0273) | (0.0281) | (0.0283) |
| L3.damage | 0.0108 | 0.0082 | 0.0011 | 0.0016 | -0.0013 | -0.0052 |
| | (0.0123) | (0.0129) | (0.0146) | (0.0167) | (0.0175) | (0.0182) |
| L4.damage | | 0.0218 | 0.0174 | 0.0177 | 0.0154 | 0.0112 |
| | | (0.0234) | (0.0243) | (0.0258) | (0.0258) | (0.0253) |
| L5.damage | | | 0.0269 | 0.0272 | 0.0244 | 0.0201 |
| | | | (0.0238) | (0.0253) | (0.0255) | (0.0247) |
| L6.damage | | | | -0.0113 | -0.0140 | -0.0204 |
| | | | | (0.0288) | (0.0279) | (0.0268) |
| L7.damage | | | | | -0.0044 | -0.0108 |
| | | | | | (0.0365) | (0.0342) |
| L8.damage | | | | | | -0.0012 |
| | | | | | | (0.0367) |
| Sum of past damages | 0.0078 | 0.0027 | -0.0102 | -0.0093 | -0.0166 | -0.0336 |
| | (0.0281) | (0.0301) | (0.0332) | (0.0375) | (0.0377) | (0.0358) |
| Log GDP per capita | 0.1785 | 0.1751 | 0.1678 | 0.1603 | 0.2226 | 0.3628 |
| | (0.6341) | (0.6285) | (0.6179) | (0.6582) | (0.6794) | (0.6814) |
| Institution index | 0.0545 | 0.0577 | 0.0647 | 0.0646 | 0.0657 | 0.0694 |
| | (0.0632) | (0.0621) | (0.0609) | (0.0607) | (0.0600) | (0.0583) |
| Log patent apps | 0.1986 | 0.2297 | 0.3079 | 0.3055 | 0.3263* | 0.3805** |
| | (0.2066) | (0.2055) | (0.1931) | (0.1892) | (0.1830) | (0.1740) |
| Observations | 503 | 503 | 503 | 503 | 503 | 503 |
| sum of damages | 0.146** | 0.157* | 0.161 | 0.152 | 0.130 | 0.096 |
| | (0.0608) | (0.0851) | (0.1136) | (0.1483) | (0.1838) | (0.2139) |
| AIC | 1257.304 | 1256.062 | 1250.880 | 1250.866 | 1250.263 | 1245.607 |
| BIC | 1350.157 | 1348.915 | 1343.733 | 1343.719 | 1343.116 | 1338.460 |

Robust standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

## Appendix 5. Further Sensitivity Analysis

The reduced form models presented in the paper use damage lagged 6 years to avoid endogeneity concerns. The instrumental variables model include instruments for damage, and thus include only a one year lag so as to ease interpretation of the stock variable. However, this may lead to changes in the lagged damage coefficients, since the lagged values in the reduced form equation include both the direct effect of the event on innovation and the indirect effect of the lagged event changing the existing knowledge stock.

To assess whether moving from a six-year lag to a one-year lag affects the results, Tables A5-A6 present three results. For each technology, column (1) is the reduced form results presented in Tables 3 or 4 (corresponding to column 1 in those tables). Columns (2) & (3) use instrumental variables for knowledge and deaths (or damages). Column (2) uses the six-year lagged knowledge stock, and column (3) uses the one-year lagged knowledge stock, as in column (2) for each technology in Tables 3 and 4.[26] In all cases, the results are similar. Moreover, the sum of deaths or damages is larger in both columns (2) and (3) for all cases except flood control (where the results are insignificant), suggesting that it is the use of instrumental variables, and not changing the lagged knowledge stock, that leads to slightly larger estimates.

[26] No results are presented for drought-resistant crops, as the model using instruments with the six-year knowledge stock did not converge to a solution.

**Table A5. Further Sensitivity Analysis: Deaths as Independent Variable**

| | Quake-Proof Building | | | Earthquake Detection | | |
|---|---|---|---|---|---|---|
| | **Baseline** | **IV** | **IV** | **Baseline** | **IV** | **IV** |
| death | 0.0149*** | 0.0158*** | 0.0139*** | 0.0130*** | 0.0131*** | 0.0131*** |
| | (0.00540) | (0.00492) | (0.00368) | (0.00224) | (0.000945) | (0.000690) |
| L1.death | 0.00821 | 0.00921* | 0.000765 | 0.00951*** | 0.0104*** | 0.0102*** |
| | (0.00653) | (0.00482) | (0.00695) | (0.00248) | (0.00202) | (0.00111) |
| L2.death | 0.0242* | -0.0255 | -0.00177 | -0.00736 | 0.0605 | 0.0539 |
| | (0.0130) | (0.0629) | (0.0556) | (0.0221) | (0.0429) | (0.0561) |
| L3.death | 0.0123 | 0.0797 | 0.106 | -0.00297 | 0.107 | 0.101 |
| | (0.0183) | (0.0728) | (0.0909) | (0.0203) | (0.0877) | (0.142) |
| l4.death | 0.0471 | 0.0226 | 0.0182 | -0.0546 | 0.0216 | 0.0154 |
| | (0.0336) | (0.0571) | (0.0569) | (0.0652) | (0.0417) | (0.0886) |
| L5.death | 0.0800*** | 0.108*** | 0.101** | -0.104 | -0.0710 | -0.077*** |
| | (0.0209) | (0.0320) | (0.0395) | (0.0674) | (0.0622) | (0.0135) |
| Sum of deaths | 0.187*** | 0.210* | 0.239*** | -0.147 | 0.141*** | 0.117 |
| | (0.0561) | (0.1126) | (0.0830) | (0.1332) | (0.0507) | (0.2546) |
| lag6_dstock | 0.265 | 0.294 | | -0.262 | 0.0428 | |
| | (0.224) | (0.270) | | (0.166) | (0.386) | |
| lag1_dstock | | | 0.662* | | | 0.0163 |
| | | | (0.354) | | | (0.291) |
| Log GDP per capita | 1.904* | 3.022** | 2.703** | 0.622 | 1.994 | 2.077 |
| | (1.056) | (1.184) | (1.073) | (1.082) | (2.310) | (1.807) |
| Institutional index | 0.00817 | 0.0415 | 0.121 | 0.0941 | 0.0791 | 0.0743 |
| | (0.0622) | (0.0926) | (0.114) | (0.110) | (0.184) | (0.152) |
| Log patent apps | 0.317* | -0.194 | -0.345 | 0.343 | -0.369 | -0.383 |
| | (0.179) | (0.417) | (0.311) | (0.413) | (0.689) | (0.594) |
| Observations | 717 | 703 | 703 | 338 | 327 | 327 |
| e(Q) | 0.0000 | 0.0712 | 0.0827 | 0.0000 | 0.2053 | 0.2053 |
| Countries | 30 | 30 | 30 | 15 | 15 | 15 |
| Time Span | | 1984-2009 | | | 1984-2009 | |

**Table A6. Further Sensitivity Analysis: Damages as Independent Variable**

| | Quake-proof Building | | | Earthquake Detection | | | Flood Control | | |
|---|---|---|---|---|---|---|---|---|---|
| | Baseline | IV | IV | Baseline | IV | IV | Baseline | IV | IV |
| damage | 0.00443 | 0.0123*** | 0.0124*** | 0.00847*** | 0.0111*** | 0.0108*** | 0.0476*** | 0.00218 | 0.111** |
| | (0.00380) | (0.00379) | (0.00193) | (0.00189) | (0.00111) | (0.000827) | (0.0123) | (0.0339) | (0.0462) |
| L1.damage | 0.00322 | 0.00687* | 0.00336 | 0.00461*** | 0.00941*** | 0.00781*** | 0.0414*** | -0.0169 | 0.0442** |
| | (0.00196) | (0.00401) | (0.00223) | (0.00172) | (0.00132) | (0.00109) | (0.0157) | (0.0480) | (0.0185) |
| L2.damage | 0.00286** | 0.000606 | 0.00133 | 0.00358* | 0.00794*** | 0.00576** | 0.0323*** | -0.0270 | 0.0309 |
| | (0.00144) | (0.00193) | (0.00135) | (0.00198) | (0.00160) | (0.00289) | (0.00954) | (0.0474) | (0.0643) |
| L3.damage | 0.00474*** | 0.00236 | 0.00324 | 0.000752 | 0.00237 | 0.00113 | 0.0111 | -0.00403 | 0.0473 |
| | (0.00100) | (0.00271) | (0.00310) | (0.00318) | (0.00206) | (0.00428) | (0.00948) | (0.0181) | (0.0376) |
| L4.damage | 0.00280** | 0.000803 | 0.00110 | 0.000666 | 0.00302 | 0.00185 | 0.0121* | -0.00921 | -0.0898** |
| | (0.00133) | (0.00141) | (0.00152) | (0.00230) | (0.00185) | (0.00264) | (0.00681) | (0.0402) | (0.0408) |
| L5.damage | 0.00297*** | 0.00364*** | 0.00332** | -0.00295 | -0.000347 | -0.0018*** | 0.00492 | 0.0449** | 0.0719 |
| | (0.00101) | (0.00111) | (0.00135) | (0.00227) | (0.00160) | (0.000406) | (0.00497) | (0.0183) | (0.0490) |
| Sum of damages | 0.021*** | 0.027*** | 0.025*** | 0.015 | 0.033*** | 0.026*** | 0.149*** | -0.010 | 0.215 |
| | (0.0081) | (0.0096) | (0.0048) | (0.0115) | (0.0034) | (0.0093) | (0.0530) | (0.1500) | (0.2038) |
| L6.log stock | 0.195 | 0.222 | | -0.129 | 0.303 | | 0.146* | 0.792*** | |
| | (0.222) | (0.291) | | (0.245) | (0.258) | | (0.0768) | (0.195) | |
| L1.log stock | | | 0.565** | | | 0.313* | | | 0.104 |
| | | | (0.242) | | | (0.175) | | | (0.343) |
| Log GDP per capita | 1.710** | 2.077* | 1.650* | 0.444 | 0.0852 | 0.930 | 1.843** | 0.648 | -1.319 |
| | (0.749) | (1.141) | (0.929) | (0.983) | (1.455) | (1.388) | (0.785) | (5.280) | (7.648) |
| Institutional Index | 0.0290 | 0.0117 | 0.0612 | 0.0432 | 0.0164 | -0.00290 | 0.306** | 0.368 | 0.367 |
| | (0.0499) | (0.0871) | (0.0805) | (0.0787) | (0.201) | (0.143) | (0.135) | (0.555) | (0.252) |
| Log Patent Apps | 0.417*** | 0.0492 | -0.0950 | 0.301 | 0.0187 | -0.240 | 0.400 | 0.0944 | 2.316 |
| | (0.150) | (0.432) | (0.295) | (0.346) | (0.506) | (0.524) | (0.254) | (1.300) | (1.837) |
| Observations | 717 | 703 | 703 | 338 | 327 | 327 | 459 | 383 | 383 |
| e(Q) | 0.0000 | 0.0704 | 0.0817 | 0.0000 | 0.2188 | 0.2259 | 0.0000 | 0.0205 | 0.0245 |
| Countries | 30 | 30 | 30 | 15 | 15 | 15 | 21 | 20 | 20 |
| Time Span | | 1984-2009 | | | 1984-2009 | | 1986-2009 | 1986-2006 | 1986-2006 |

Standard errors in parentheses *** p<0.01, **p<0.05, *p<0.1

## Appendix 6. Instrument Quality

To assess the quality of our instruments, Table A7 includes the partial $R^2$ and Shea partial $R^2$ statistics for each of our endogenous variables for each technology. With multiple endogenous variables, simply assessing the F-statistic of the excluded instruments is not a sufficient test of the strength of the instrument (Baum 2006). Shea's partial $R^2$ statistic accounts for the intercorrelations among instruments. If the Shea partial $R^2$ is significantly smaller than the standard partial $R^2$, it suggests that there are not enough unique instruments to identify each endogenous variable. As we see in Table A1, that is not the case, as both partial $R^2$ values are similar for each variable.

However, as discussed in the text, the instruments for flood control and drought-resistant crops are weak, as the partial $R^2$ values are below 0.05 for nearly all variables. Thus, for these technologies we have more faith in our reduced form regressions. Given that there are few differences between the reduced form and instrumental variable results when the instruments are stronger in the case of earthquake, we do believe that these reduced form estimates are valid.

**Table A7. Partial $R^2$ Statistics**

| | *Earthquake Buildings* | | *Earthquake Detection* | | *Flood Control* | | *Drought-Resistant Crops* | |
|---|---|---|---|---|---|---|---|---|
| | partial R2 | Shea partial R2 | partial R2 | Shea partial R2 | partial R2 | Shea partial R2 | partial R2 | Shea partial R2 |
| Deaths(t) | 0.3457 | 0.3984 | 0.4227 | 0.4594 | 0.0187 | 0.0278 | | |
| Deaths(t-1) | 0.2880 | 0.3666 | 0.3913 | 0.4301 | 0.0124 | 0.0240 | | |
| Deaths(t-2) | 0.1893 | 0.2038 | 0.3729 | 0.3732 | 0.0149 | 0.0201 | | |
| Deaths(t-3) | 0.2138 | 0.2293 | 0.3928 | 0.3938 | 0.0163 | 0.0220 | | |
| Deaths(t-4) | 0.2068 | 0.2374 | 0.3701 | 0.3883 | 0.0184 | 0.0281 | | |
| Deaths(t-5) | 0.1924 | 0.2409 | 0.3902 | 0.4420 | 0.0112 | 0.0205 | | |
| Knowledge Stock (t-1) | 0.0731 | 0.0789 | 0.3455 | 0.3625 | 0.1431 | 0.1608 | | |
| | | | | | | | | |
| Damages(t) | 0.2844 | 0.2980 | 0.3433 | 0.3489 | 0.0417 | 0.0478 | 0.0861 | 0.1044 |
| Damages(t-1) | 0.2485 | 0.2908 | 0.3291 | 0.3463 | 0.0401 | 0.0463 | 0.0420 | 0.0530 |
| Damages(t-2) | 0.1980 | 0.2102 | 0.2575 | 0.2662 | 0.0376 | 0.0563 | 0.0380 | 0.0416 |
| Damages(t-3) | 0.2098 | 0.2224 | 0.2910 | 0.2925 | 0.0410 | 0.0555 | 0.0410 | 0.0477 |
| Damages(t-4) | 0.2309 | 0.2431 | 0.3074 | 0.3150 | 0.0396 | 0.0484 | 0.0396 | 0.0523 |
| Damages(t-5) | 0.2444 | 0.2747 | 0.3340 | 0.3566 | 0.0392 | 0.0475 | 0.0339 | 0.0489 |
| Knowledge Stock (t-1) | 0.0661 | 0.0789 | 0.3602 | 0.3625 | 0.1446 | 0.1608 | 0.0769 | 0.1185 |

**Appendix References**

Baum, C.F. (2006). *An Introduction to Modern Econometrics Using Stata*. Stata Press: College Station, TX.