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CLIMATE CHANGE ADAPTATION, NATURAL HAZARD MITIGATION, AND INNOVATIVE RESPONSES

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ABSTRACT

This dissertation is comprised of three essays which examine innovation, both technological and institutional, as a response aimed to adapting to climate change and natural disasters. Specifically, the first two papers seek to understand the drivers and implications of adaptation-related technological innovations. The third paper draws on the policy innovation theory to examine factors that shape the decision of state governments to engage in comprehensive climate adaptation planning.

In Chapter 1, I examine the drivers of technical innovation as an important form of adaptation by investigating the impact of three types of natural disasters—floods, droughts and earthquakes—on the patenting activities of their respective mitigation technologies. Using patent and disaster damage data, this study is the first to empirically examine adaptation responses across multiple sectors at the country level. My empirical analysis, using a panel of 28 countries over a period of 25 years, shows that a country's risk-mitigating innovations increase significantly with the severity of disasters it has recently experienced, while the degree of impact varies across different types of disasters and technologies.

In Chapter 2, I evaluate the effectiveness of the risk-mitigating innovations in reducing disaster impacts in the case of earthquakes. By conceptualizing adaptation as a learning process, I examine the effect of technical knowledge stocks, constructed by patent counts in quake-proof building technologies, and informal knowledge, measured by prior earthquake experiences, on reducing earthquake-related losses. Using a global cross section, I find that countries with more earthquake-

mitigation technical innovations and more earthquake exposure in the past suffer fewer fatalities. This “learning-by-doing” effect is much larger in high-income countries, which suggests their stronger adaptive capacity.

Finally, Chapter 3 focuses on climate adaptation planning in the U.S. by examining the factors that drive state governments to develop comprehensive adaptation plans. I use an event history analysis to examine both internal factors (states’ climate risks, adaptive capacity and political interests in climate change) and policy diffusion among states within the same climate regions. This study finds that the state-level adaptation decision is highly driven by the extreme weather events the state has recently experienced, and also associated with the state’s potential exposure to climate risks, income level, civic engagement and environmental preferences. By examining the motivation for and barriers to subnational adaptation responses, this research has important implications for environmental federalism and governance.

From the innovation perspective, my dissertation contributes to a deeper understanding of adaptation as a dynamic social-learning process, and sheds light on what drives society to adapt to environmental changes and shocks. It also informs an integrated policy approach to facilitating efficient climate adaptation and natural hazard mitigation.

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INTRODUCTION TO THE DISSERTATION

Given the growing scientific consensus that climate change is taking place and will worsen in the future, adaptation has been increasingly recognized as an essential strategy to reduce the unavoidable impacts of climate change. As a matter of fact, adaptation is not something new. It is a process of making "deliberate changes in anticipation of or in reaction to external stimuli and stress" (Nelson et al., 2007). Historically, human societies have always been adapting to environmental changes and shocks in various ways, including relocation, building defenses, and changing the crops they cultivated. However, the current rate of global climate change caused by rapidly increasing greenhouse gas (GHG) emissions is much faster than before, which results in significant and unevenly distributed impacts on society and nature. Therefore, how to facilitate efficient and effective societal adaptation and also improve our adaptive capacity to cope with climate change and related disasters are important policy questions.

This dissertation examines examples of both historic adaptation to natural disaster at the global level and more recent adaptation initiatives of subnational governments in order to better understand the motivations and implications of various adaption responses, and also to shed light on adaptation policy making. It consists of three empirical papers which are linked by a common theme of adaptation and innovation. The underlying notion is that successful adaptation requires forward thinking and innovation, both technological and institutional (Rodima-Taylor et al., 2011); at the same time, innovation can be viewed as a social learning process reflecting human adaptation to their changing needs and environment. The ability to innovate, to a large extent, determines the capacity of society to adapt to environmental changes. Specifically, the first two chapters focus on *technological innovation*, by examining how innovators respond to natural disasters and how innovation and diffusion of new risk-mitigating technologies may help mitigate disaster impacts. The third chapter considers adaptation planning as a *policy innovation*, and explores the factors that drive the U.S. state governments to make comprehensive plans for climate adaptation.

The first chapter is concerned with what motivates and enables adaptation responses. Since technology development provides an important means for people to adjust to environmental changes (e.g., the invention of air conditioning), I focus on the innovation of risk-mitigating technologies as an outcome of adaptation and investigate whether and how innovation responds to the shock of natural disasters. The key question underlying this research is whether the recent disaster experiences raise the perceived risks and induce the private sector to develop new technologies to meet the higher demand for adaptation.

My empirical analysis focuses on three types of natural disasters – floods, droughts, and earthquakes – and pair each of them with one mitigation technology, including flood control, drought-resistant crops and quake-proof buildings. Drawing upon the literature on induced innovation and the economics of natural disasters, I model a country's annual patent flow in a given technology field as a function of a distributed lag of recent disaster impacts (measured by fatalities and monetary damages), its existing knowledge stocks and other socioeconomic characteristics that may affect its adaptive capacity, controlling for the unobserved country heterogeneity. Considering the potential endogeneity of knowledge stocks and disaster impacts, I use meteorological and geophysical data to create hazard intensity measures as instrumental variables. I find that all three types of natural disasters have a significant and positive impact on the patenting of their corresponding technologies. I also examine whether domestic innovation can be induced by foreign nearby disaster shocks, and find such evidence in the case of floods.

Overall, the study in Chapter 1 informs climate adaptation policy with empirical evidence that the private sector is adapting reactively rather than proactively, which suggests that government has an important role to play in supporting the development of these technologies before an event occurs. It also informs modeling of future climate change damages by suggesting that climate adaptation should not be treated as an autonomous process, but rather as a function of previous disaster damages.

While Chapter 1 focuses on innovation as a response to natural disasters, it says little about the effectiveness of these technical innovations in mitigating future disaster risks. The latter question is then examined in the second chapter, in which I conceptualize adaptation as a social learning process, and knowledge as an important component of adaptive capacity. While the existing literature on the determinants of disaster damage has mainly focused on the aggregated effects of income and institutions, I extend this line of research by investigating the extent of adaptation to earthquakes with a particular focus on the role of technology development and social learning. Specifically, I examine the mitigating effect of a country's technical knowledge (constructed using patent counts in quake-proof building technologies) and prior earthquake exposure, considering the latter as not only a driver of learning but also a proxy for informal knowledge related to earthquake preparation and mitigation.

One empirical challenge in this research is that a large proportion of the earthquakes recorded in the database have missing values for damages. To address this issue, I used multiple estimation strategies, including censored regressions and Heckman selection model, which produce consistent estimation results. My empirical analysis, using a global cross section of 894 earthquakes in 79 countries between 1980 and 2010, shows that the accumulation of technical knowledge and past experiences leads to significant reduction in earthquake-induced fatalities. Moreover, the effect of prior earthquake experiences is more pronounced for developed countries, suggesting their stronger adaptive capacity. Given the public good nature of innovations, I also examine whether foreign knowledge can help reduce disaster impacts but do not find strong evidence on the knowledge spillover effects. These findings highlight the importance of incorporating technological innovation as part of a long-term disaster mitigation and adaptation policy, and also suggest the need for more policy efforts at the international level to facilitate the diffusion and transfer of risk-mitigating technologies across countries.

Finally, the third chapter focuses on adaptation planning as an institutional innovation emerging rapidly at different levels of government, and examines the factors that drive state governments to develop comprehensive plans for adapting a variety of sectors to climate change. This research is motivated by a growing literature studying the development and diffusion of GHG mitigation policy at the subnational levels, but is much less concerned with climate adaptation.

This paper is the first to empirically examine the development of state-level adaptation policy from a planning perspective.

Drawing upon the policy innovation literature, I hypothesize that states' adaptation planning initiatives are driven by internal determinants, including a state's climate risks, adaptive capacity, and political interests in climate change, as well as the external influence from other nearby states. I use a discrete-time event history analysis to model the likelihood that a state initiates the planning process in a given year. This study shows that a state is more likely to pursue adaptation planning if it has experienced severe extreme weather events in the past two years. I also find that states' adaptation decisions are affected by their potential exposure to climate risks (e.g., length of ocean coastline, size of coastal economy, and forest coverage), income level, civic engagement, and general environmental preferences. I do not find strong evidence on regional diffusion of adaptation planning among states.

This research contributes to a deeper understanding of the motivation for and barriers to subnational adaptation decisions. My results further suggest that state-level adaptation actions strongly reflect inequality in state economic conditions, implying the need for more federal coordination and support.

In sum, this dissertation seeks to understand the dynamics of societal adaptation in order to inform climate adaptation policy and the estimation of future climate change damages. My studies suggest that (1) adaptation is not autonomous. It is motivated by the impacts of salient environmental shocks and also shaped by socioeconomic factors; and (2) effective adaptation can mitigate the impact of environmental changes on societies, while the capacity to undertake effective adaptation varies considerably across regions which may reinforce the vulnerability of those disadvantaged communities. Given the reactive nature of adaptation responses, it is crucial for policy makers to encourage proactive adaptation in both public and private sectors, with special attention devoted to those socially vulnerable areas. It is equally important to account for the endogeneity and dynamics of adaptation in climate modeling to appropriately estimate the costs of climate change.

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Chapter 1: Necessity as the Mother of Invention: Innovative Responses to Natural Disasters[1]

1. Introduction

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

In this paper, we ask whether natural disasters lead to innovations of risk-mitigating technologies. Such technologies are analogous to those that may aid adaptation to climate change and associated natural disasters. Specifically, we coin the term "risk-mitigating innovation," referring to the *development of new and more effective technologies that assist people in better coping with natural disasters and building resilience to future shocks*. Such innovation may include both the development of new products and the improvement and commercialization of existing technologies to make them more appealing for consumers to adopt. Technological innovation is an important form of adaptation because it provides the necessary tools for people to utilize in adapting to a changing environment. Although adaptation in some cases can be just behavioral changes (e.g., relocation), people more often have to employ certain technologies,

[1] This paper is published in the *Journal of Environmental Economics and Management*. It is cited in the following two chapters of this dissertation as Miao and Popp (2014).
[2] A term initially used to explain biological evolution, adaptation is now applied more often to human society and regarded as an important strategy to address climate change (for a review on the concept, see Smit and Wandel, 2006). The IPCC defines adaptation as "*adjustment in natural or human system in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities*" (IPCC TAR, 2001: 72).

which take either a hard form (e.g., equipment and infrastructure such as building levees) or a soft form (e.g., science, technical know-how and skills such as emergency management) (UNFCC, 2006). Technological innovation enhances their capacity to cope with natural hazards and provides a long-term adaptation strategy.

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

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

Another contribution of this paper is to explore the motivation and ability for adaptation responses, which is an under-researched issue in the adaptation literature. Notably, a majority of the current adaptation studies focuses on estimating costs or cost-effectiveness of adaptation measures, and many climate models simply treat adaptation as autonomous. For instance, recent examples of climate policy models incorporating adaptation are the AD-DICE model (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.

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

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

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

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature. Section 3 presents a conceptual framework, followed by our empirical model. Section 4 describes our data sources and descriptive statistics. Section 5 discusses the empirical results and Section 6 concludes.

2. Relevant Literature

This paper is part of a growing literature on the economics of natural disasters (for a survey of the literature, see Cavallo and Noy, 2010 and Kellenberg and Mobarak, 2011). This literature consists of two bodies of research that are highly related but differ regarding the treatment of disaster variables: one concerning the economic effects of natural disasters, and the other assessing the determinants of natural disaster impacts. While this study falls into the former category by considering how natural disasters affect innovation, we also draw on the latter research to address the endogeneity of disaster damages. We discuss the relevant literature on the determinants of natural disaster impacts while developing our conceptual framework in section 3.

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

Our research question also draws on the hypothesis of induced innovation, which posits that changes in the relative price of an input of production lead to innovations that enable reducing the use of the relatively more expensive factors (Hicks, 1932). Over the past decade, this theory has been examined by environmental economists to understand the relationship between energy prices, environmental regulations and innovations of environmental technologies (for an overview of this topic see Popp, 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 innovations. Similar empirical evidence on the responsiveness of innovations to energy prices and environmental regulations has been found

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

by other researchers using other modeling techniques (e.g., Newell et al., 1999) and conducting cross-national analyses (e.g., Johnstone et al., 2010; Verdolini and Galeotti, 2011).

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

3. Modeling

3.1 Conceptual framework

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

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

Drawing on this line of research, we model the unobserved perceived risk (R_{it}) as a function of the recent shocks country i has experienced, indicated by a distributed lag of disaster damages (D), a country's capacity to cope with and adapt to natural disasters (C_{it}), and the country's baseline hazard (H_i) (e.g., does the country have a fault line?). Based on the risk perception literature surveyed above, we expect risk perceptions to depend on the severity of disaster damages (e.g., human and economic losses from natural disasters) rather than the frequency or magnitude of such events.[7]

$$R_{it} = f\left(\sum_{n=0}^{N} D_{it-n}\,,\, C_{it}\,,\, H_i\right) \tag{3.1}$$

The baseline hazard is important for perceived risk, because people living in a region known

[6] More specifically, the protection motivation theory discusses four cognitive factors falling on two dimensions: risk appraisal includes the perceived severity of threatening events and the perceived probability of the occurrence, while the perceived efficacy includes the efficacy of the protective measures and the perceived self-efficacy in coping with a threat. The empirical research, such as Grothmann and Patt (2005), draws on this theory to examine the cognitive factors that influence people's adaptive behavior.
[7] The rationale is simple: if a natural disaster of an extremely high magnitude occurs in an uninhabited area and results in little damage, it may not substantially affect people's risk perception.

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

Equation (3.1) raises two additional conceptual issues: first, adaptive capacity is unobserved and often related to national attributes; and second, a country's adaptive capacity also influences the impact of a disaster shock it has experienced. To illustrate this further, we draw on the natural hazards and vulnerability literature, which suggests the actual disaster impact depends on both the physical severity of the hazard and local vulnerability or adaptive capacity (Yohe and Tol, 2002; Brooks et al., 2005; IPCC, 2012), with the latter being socially determined and place based. In other words, the same natural hazard occurring in different places will result in different impacts because some people and communities are more susceptible to hazards than others (Kousky, 2012; Cutter et al., 2003).

In line with the notion of vulnerability and adaptive capacity is a series of empirical studies examining the determinants of natural disaster impacts. Using a cross-national, multi-hazard data set, Kahn (2005) shows that nations with higher income and more democratic institutions suffer

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

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

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

fewer deaths from natural disasters. He argues that economic development and good institutions lead to better infrastructure and preventive technologies, as well as more effective regulations and emergency management, which provide "implicit insurance" against natural disasters. Subsequent studies have examined a variety of institutional measures, including inequality (Anbarci et al., 2005), corruption (Escaleras et al., 2006), political regime (Keefer et al., 2010) and governance (Ferreira et al., 2013) as well as different patterns of the damage-income relationship (Toya and Skidmore, 2007; Kellenberg and Mobarak, 2008; Schumacher and Strobl, 2011; Hallegatte, 2012) to account for cross-national heterogeneity in the disaster fatalities. Based on this literature, we model disaster impact (D_{it}) as a function of the physical magnitude of disaster shocks (M_{it}) and the country's adaptive capacity (C_{it}).

$$D_{it} = f(M_{it}, C_{it}) \tag{3.2}$$

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

$$C_{it} = f(Y_{it}, I_{it}, K_{it-1}) \tag{3.3}$$

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

Finally, innovation itself depends on the perceived risk (R_{it}), a country's existing knowledge base (K_{it-1}), income (Y_{it}), and science base (S_{it}).

$$PAT_{it} = f(R_{it}, K_{it-1}, Y_{it}, S_{it}) \tag{3.4}$$

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

Combining equations (3.1), (3.3) and (3.4) to remove unobserved risk and capacity provides the following relationship:

$$PAT_{it} = f(\sum_{n=0}^{N} D_{it-n}, H_i, K_{it-1}, Y_{it}, I_{it}, S_{it}) \tag{3.5}$$

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

Second, although we expect a positive relationship between disaster damages and innovations, the effect of variables measuring adaptive capacity are ambiguous. Equations (3.1), (3.2) and (3.3) suggest that both a greater existing knowledge stock and higher income increase adaptive capacity, thus reducing the perceived risks and also the need for additional innovations.[11] At the same time,

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

equation (3.4) suggests existing knowledge serves as a building block for future innovations. Although the existing knowledge may inspire more innovations, it may also be the case that a strong existing stock may constrain technological opportunities and make future breakthroughs more difficult. Similarly, because innovation is primarily carried out in industrialized countries, and people from higher-income countries may have a higher demand for risk-mitigating technologies, a positive correlation between income and patenting activity is also possible.

Finally, equation (3.2) suggests that the observed damages experienced by a country are simultaneously determined by both the physical magnitude of the disasters and the country's adaptive capacity. As capacity is unobserved, but is a function of income, institution and existing knowledge, the resulting damages are thus endogenous. Nonetheless, our theory posits that disasters have their effect on risk perceptions via the damages they cause. Therefore, damages from recent natural disasters remain the key variable of interest in our conceptual and empirical model. In the following section we discuss how we address the endogeneity issue in our empirical work.

3.2 Empirical model

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

$$PAT_{jit} = f\left(\sum_{n=0}^{n_j} D_{it-n}, Y_{it}, I_{it}, K_{jit-1}, S_{it}, \eta_i, \theta_t\right) \tag{3.6}$$

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

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

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

However, estimating this model raises two endogeneity concerns. First, as discussed earlier, the damages a country suffers from disasters are potentially endogenous to its socio-economic

[12] The impact of the Fukushima nuclear disaster on preferences for nuclear power around the world provides an example of how large natural disasters can affect global risk perception.
[13] Because of the panel nature of the data, we do not use a negative binomial model, because the negative binomial fixed effect model does not truly control for unobserved fixed effects (Alison and Waterman, 2002; Cameron and Trividi, 2005; Paulo, 2008).
[14] Unless we can find proper measures for the country specific heterogeneity and include them in the regression, the potential correlation between the observed fixed components η_i with the other regressors would make a standard random effects estimator inconsistent.

status. Although the country fixed effects control for the time-invariant characteristics, they cannot account for those time-varying elements of a country's adaptive capacity that may affect disaster outcomes and innovation responses simultaneously. The latter would cause omitted variable bias for our disaster variables and presumably lead the estimated effect of disaster damages on innovation to be negatively biased. Second, our lagged knowledge stock variable is also endogenous, as it is, in part, simultaneously determined by the lagged damages included in our model.

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

4. Data

In this study we create a balanced panel of up to 28 countries (depending on the technologies) for the period 1984-2009, with variables measuring risk-mitigating innovations, disaster impacts and

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

country characteristics. The data are taken from a variety of sources, described in greater detail below. As noted earlier, we consider three separate risk-mitigating technologies: flood control, drought-resistant crops and quake-proof buildings. The choice of technologies and disasters studied is influenced by the availability of both adequate data on disaster impacts and clearly identifiable technologies in the patent data.

4.1 Innovation and knowledge stocks

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

It is important to acknowledge that patents, while a common measure of invention used in the innovation literature, are not a perfect measurement (Griliches, 1990; Motohashi and Goto, 2010). There are two major shortcomings of using patent data: first, the number of patent applications in

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

a country is highly subject to its patent system. Thus, we control for country heterogeneity by including the overall number of patents in each country in our regression. Second, not all inventions get patented. Inventors have the right to hide or reveal their inventions. Because the propensity to patent varies by technology, we do separate regressions for each technology so our identification strategy focuses on patenting changes within a single technology.

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

$$K_{jit} = PAT_{jit} + (1- \rho)\, K_{jit-1} \tag{4.1}$$

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

4.2 Disaster data

We measure disaster severity, our key independent variable, using both human fatalities and economic losses from the natural disasters, with data taken from two sources. We use drought and floods data from the Emergency Event Database (EM-DAT) maintained by the Centre for Research on the Epidemiology of Disaster. Although this database is publically assessable and used in most

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

cross-country disaster studies, the accuracy of its data has been questioned given its humanitarian focus and specific thresholds for events to be included.[18] Although we can identify no better alternative for information on flooding and droughts, we collect data on earthquakes from the National Geophysical Data Center's (NGDC) Significant Earthquake Database.[19] This database is preferred to EM-DAT because it contains richer information on earthquake physics (e.g., magnitude and Modified Mercalli Intensity), much longer timespan and more small-impact events that do not meet the EM-DAT threshold. All the monetary losses from disasters are adjusted at the 2005 level by the World Bank GDP deflator index.[20]

4.3 Instrumental variables

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

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

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

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

1 through year *t*-25, with some variables already being included in the set of instruments for disaster impacts. The relevance of all the instrumental variables is presented in Appendix Table 1-A5.

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

We create additional variables to capture the physical intensity specific to these two disasters. For floods, considering that the rainfall anomaly variable does not fully account for the temporal variation of rainfall within a year, we use the same data set to create another variable measuring the number of months in which the amount of precipitation exceeds 150 percent of the long-term average monthly precipitation. Moreover, given the fact that many flooding events are induced by storms, we calculate the number of storms (including tropical storms, subtropical storms and extratropical storms) a country experienced in a given year, using storm data from the International Best Tract Archive for Climate Stewardship (IBTrACS) provided by the National Climate Data Center of the National Oceanic and Atmospheric Administration (NOAA). The IBTrACS data, which are compiled from numerous tropical cyclone datasets, provide the most complete global set of individual storm events and track its positions (latitude and longitude) at 6-hour intervals.

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

We use geospatial software to map the storm data to affected countries and calculate the frequency of storm events within a country in a given year. For drought, given its chronic nature, we follow Felbermayr and Groschl (2013) and create a drought indicator (also using the precipitation data from Tyndall Center), which takes the value of 1 if a country's precipitation is below 50 percent of the long-run average monthly mean in at least three subsequent months or at least five months within a year (zero otherwise).

For earthquakes, we use the Richter scale, provided in the NGDC database, as a strength measure of seismic activities. One issue arising here is that the original database records individual earthquake events, which differs from the unit of observation in our panel. We thus collapse the events data to the country-year level and construct three variables to measure the physical intensity of earthquakes: a dummy variable indicating whether there is an earthquake in a country in a given year, the maximum magnitude of all earthquakes in a country in a given year, and the total number of earthquakes measuring six and above on the Richter scale in each country per year. [22]

4.4. Country characteristics

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

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

for this country characteristic. The data come from the World Bank World Development Indicators and the database of the World Intellectual Property Organization.

4.5 Sample statistics

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

Table 1-2 provides national summary statistics reporting the average deaths and damages from natural disasters per year by disaster type, and total patent counts by technology type for the period 1970-2009. A large majority of our sample countries are industrialized countries. This is consistent with the notion that most of the global R&D activities are carried out by developed countries (National Science Board, 2010) because they have higher demand and more resources for science, technology and innovation. In particular, the United States, Germany and Japan appear to play leading roles in patenting on these mitigating technologies. Notably, China seems to be most severely impacted by all three types of disasters among all sample countries, while it also has a large number of patents on these technologies. To compare across disasters, while our samples for earthquakes and floods include the major affected countries, we leave out several countries that

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

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

Table 1-3, Panel A reports the descriptive statistics of main variables in the analysis. To provide a sense of scale of the natural disasters, Panel B shows the human and economic losses on an event basis and the most damaging events over our sample period, including the affected country and year of occurrence. In terms of average damages per country and year (shown in Panel A), earthquakes and floods appear to have caused much larger losses on our sample countries than droughts. This is consistent with the statistics in Yang (2008a) that floods and earthquakes altogether accounted for about 60 percent of the total global damages from natural disasters for 1970-2002, which is ten times the drought damages. However, Panel B shows that droughts occur in our sample countries less frequently than the other two types of disasters. As noted earlier, this is partially because the countries that are often hit by droughts are not patenting and thus not included in our sample. Such results also demonstrate the importance of considering the endogeneity of damages, as one reason higher income countries report fewer drought events is that they are better equipped to deal with drought, such as through better irrigation practices. Thus, while droughts are reported less frequently in our sample countries, when a drought is reported, the average damage caused per event is highest among the three disaster types.

5. Results

5.1 Impacts from domestic disaster shocks

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

Table 1-4 presents the estimation results of our main specification using either deaths or monetary losses as the measure of disaster impacts. Because we use the Poisson model for estimation, we are able to interpret the coefficients of disaster losses in a semi-elasticity form and of other variables in logs (e.g., knowledge stock and income) as elasticities. Two things are important to note here: first, for droughts we focus on only economic damages because a majority of our sample countries have zero deaths over the estimation period, which makes it difficult to identify the effect of disaster fatalities on innovations. Second, based on our sensitivity tests (Appendices 3 and 4), we use a five-year distributed lag for earthquakes and droughts, while extending the lag structure to seven years in the case of floods.[25] We also test for serial correlation by obtaining the residuals from our estimation model, and we cannot reject the hypothesis of zero correlation between current and lagged residuals.

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

In particular, floods have an exceptionally long-term stimulating effect on flood-control innovations. At the same time, the magnitude of impacts generally declines with the passage of time, suggesting innovation is most responsive to the most recent events. The coefficients on the current-year flood impact indicate that an additional 1,000 deaths leads to a 57 percent increase in patent applications, and one billion dollars of monetary damages result in an 8.14 percent increase

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

in patent applications filed in the same year. The cumulative long-run effect of 1,000 deaths caused by flooding increases flood-control patent applications in the next seven years (including year t) by a factor of three, whereas one billion of damage increases cumulative patenting by 30 percent, with innovation mostly concentrated in the current year and the past three. While the magnitude of the effect of deaths is larger, it is important to note that monetary damages, rather than large death counts, are the primary result of flooding in the countries in our sample. To put these numbers in perspective, the 2008 Midwest flood in the United States, which resulted in around $9 billion monetary damages (above the 95th percentile for all flooding events in our sample), would increase flood control patent applications in the next seven years by 270 percent.

For earthquakes, we find that the effects of earthquakes on quake-proof building innovations are mainly spread across a six-year horizon. An additional 1,000 deaths increase the number of patent applications filed in the current year and following five years by 18.2 percent, and $1 billion economic losses from earthquakes increases the number of patent applications filed in the current year and following five years by 2.8 percent. For more concrete examples, the most expensive earthquake so far, Kobe Earthquake (Japan, 1995), incurred more than $160 billion losses, which would increase the quake-proof building patent applications in the following years by a factor of 4.5. A more moderate earthquake, such as the 1994 Northridge Earthquake that resulted in $50 billion in damages, would increase the patent applications in the following years by 140 percent.

Finally, for the drought-resistant crop technology, the effect of droughts on patenting is also positive and statistically significant in most lagged years. The cumulative effect of drought damages is the largest of our three disasters. Not only is the magnitude of the cumulative effects larger, with an additional $1 billion drought damages increasing long-run patent applications by nearly 40 percent, but the mean losses per event are larger for droughts, as shown in Table 1-2B.

To put these results in the context, a severe drought such as the US drought of 2002, which resulted in \$3.6 billion losses nationwide (around the 95^{th} percentile for all drought events in our sample), would increase drought-resistant crop patent applications in 2002-2007 by 139 percent.

As we discussed earlier, the knowledge stock can affect risk-mitigating innovations through multiple channels, thereby making its final effect somewhat ambiguous. From Table 1-4 we see the coefficients of one-year lagged knowledge stock variables are consistently significant and positive in the earthquake case: one percent increase in last year's knowledge stock leads to a 0.8-0.9 percent increase in today's patent applications. This suggests that the earlier knowledge stock serves as a building block for future innovations even after considering its possible competing effects on risk-mitigation innovations as part of a country's existing adaptive capacity. By contrast, the effects of the knowledge stock on the patenting activity for flood-control and drought-resistant crop technology are smaller and insignificant, suggesting the competing forces of knowledge as a building block and knowledge representing increased adaptive capacity at work. Likewise, income and institutional quality, as the components of a country's adaptive capacity, also have a mixed effect on risk-mitigating innovations. One possible reason is that the institutional variable exhibits little variation within countries over time for most of our sample countries. Therefore, it is not surprising to see few statistically significant results for these variables after controlling for the country fixed effects.

5.2 Impact of foreign disasters

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

While our model already controls for foreign disasters indirectly through year fixed effects, in this section we further explore the influence of foreign disasters by asking whether natural disasters occurring in nearby foreign countries are more likely than other foreign events to induce domestic risk-mitigating innovations. Nearby disasters are of interest for two reasons. First, geographic proximity leads countries to share similar environmental characteristics and similar risk profiles. Second, as flows of knowledge tend to dampen with increased distance (see, e.g. Verdolini and Galeotti, 2011), geographic proximity makes it more likely that nearby foreign countries represent a potential market for new innovations. To explore the effect of nearby disasters, we group

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

countries by continent and create variables measuring foreign disaster impacts occurring in other countries on the same continent as country *i*.[27] As with domestic disasters, we include a distributed lag of the continent-based foreign disaster variables, measured by either human or economic losses, into equation (3.6) while using the same sets of instrumental variables to instrument for domestic disaster impacts as well as the domestic knowledge stock. As our model already controls for the global effect of foreign disasters via year fixed effects, the continent-specific variables test whether nearby disasters are more likely to spur innovation than other foreign disasters.

Table 1-5 presents the estimation results. First note that the coefficients on both domestic disaster impacts and our control variables are largely similar to the results of the model only using domestic impacts (Table 1-4). The only exception is in the earthquake case the cumulative effect of domestic deaths on quake-proof building innovations over the recent five years is no longer statistically significant. In terms of foreign shocks, we only find a differential effect for foreign disasters occurring on the same continent in the case of flooding. For example, 1,000 deaths from regional foreign floods one year and two years ago would increase the domestic flood-control patent applications by 9.8 percent and 17.1 percent, respectively. We find similar results using economic damage as a disaster measure. For both deaths and damages, the cumulative long-term effect of foreign floods over the eight-year horizon (from year t through year t-7) is statistically significant, but the magnitude is much smaller than the effect of domestic influence on innovations. This finding is not surprising, and suggests that domestic disasters matter more than foreign shocks in shaping innovation responses.

By contrast, we find little evidence of a differential effect for foreign disasters on the same continent for earthquakes and droughts. The cumulative effect is statistically insignificant in both

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

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

6. Conclusion

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

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

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

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

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Table 1-1 Summary of Instrumental Variables

Technology	Instrumental Variables
Flood Control	$\sum_{n=0}^{25} anomaly_{it-n}$, $\sum_{n=0}^{25} month_{it-n}$, $\sum_{n=0}^{25} storm\_count_{it-n}$, $\sum_{n=0}^{7} Pop\_Density_{it-n}$
Quake-proof Building	$\sum_{n=0}^{25} Quake\_indicator_{it-n}$, $\sum_{n=0}^{25} Max\_magnitude_{it-n}$, $\sum_{n=0}^{25} Quake\_counts_{it-n}$, $\sum_{n=0}^{5} Pop\_Density_{it-n}$
Drought-resistant Crop	$\sum_{n=0}^{25} anomaly_{it-n}$, $\sum_{n=0}^{25} Drought\_indicator_{it-n}$, $\sum_{n=0}^{5} Pop\_Density_{it-n}$

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

Table 1-2 Natural Disaster and Patent Statistics for Sample Nations, 1970-2009

Disaster/*Technology*	**Flood**		***Flood control***	**Earthquake**		***Quake-proof Building***	**Drought**		***Drought-resistant crop***
Country	Average deaths	Average damages	Total patent counts	Average deaths	Average damages	Total patent counts	Average deaths	Average damages	Total patent counts
Argentina	.	.	.	1.93	5.5	10	.	.	.
Australia	5.08	161.28	10	0.3	0.17	12	0	405.93	39
Austria	0.98	96.13	5	0.03	0	7	0	0	6
Belarus	.	.	.	0	0	7	.	.	.
Belgium	.	.	.	0.05	2.17	8	0	0	22
Brazil	.	.	.	.	.	.	0.5	214.86	5
Bulgaria	.	.	.	0.08	0.2	8	.	.	.
Canada	0.93	64.22	16	0	0	35	0	270.53	39
China	949.33	4140.81	305	9055.73	3347.25	291	88.35	685.72	636
Czech Republic	1.85	128	46	.	.	.	.	.	.
Denmark	.	.	.	0	0	6	.	.	.
France	4.75	157.69	34	0.23	0	134	0	57.78	46
Germany	1.08	375.95	227	0	9.28	149	0	0	182
Greece	.	.	.	6.78	107.88	31	.	.	.
Hungary	7.73	21.173	10	0	0	11	0	35.03	10
India	.	.	.	.	.	.	8	78.36	7
Israel	.	.	.	.	.	.	0	2.16	23
Italy	14.43	634.39	9	152.75	1520.69	42	0	0.0263	.
Japan	28.15	329.41	415	146.35	4211.9	9928	0	0	93
Mexico	.	.	.	266	175.51	10	0	47.71	5
Netherlands	0.03	18.07	8	0.03	3.26	11	0	0	18
Norway	.	.	.	.	.	.	0	0	.
New Zealand	.	.	.	0.08	8.1	29	0	3.13	12
Poland	2.35	146.64	22	0	0	13	.	.	.
Republic of Korea	57.1	91.14	187	0	0	217	0	0	48
Romania	16.7	105.69	7	39.98	82.73	23	.	.	.
Russia	13.58	68.5	59	100.93	753.5	85	0	0	20
Spain	.	.	.	0	1.27	25	0	396.07	8
Sweden	0.28	11.49	10	0	0	6	0	0	.
Switzerland	0.25	72.26	13	0	0	12	0	0	13
Ukraine	.	.	.	0	0	22	.	.	.
United Kingdom	1.23	415.47	89	0	0	33	0	0	15
United States	35.5	1356.08	91	5.68	1406.02	323	0	203.8	864
Total	1141.33	8394.393	1563	9775	11629.93	11478	96.85	2401.1063	2111

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

Table 1-3 Descriptive Statistics
(Panel A)

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

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

Table 1-3 (Panel B) - Statistics on Disaster Events

Disaster	**Floods**	**Earthquakes**	**Droughts**
Frequency in sample countries	672	493	55
Mean deaths per event	63.61	238.26	
Mean monetary loss per event (2005 b US$)	0.486	0.874	0.966
Max. deaths	6,303	87,724	
	China-1980	China-2008 (*Wenchuan Earthquake*)	
Max. monetary loss (2005 US$, billion)	37.09	161.13	17.21
	China-1998	Japan-1995 (*Kobe Earthquake*)	China-1994

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

Table 1-4 Innovation in Response to Domestic Shocks

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

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

Table 1-5 Innovation in Response to Domestic and Foreign Shocks

Technology	***Flood Control***		***Quake-proof Building***		***Drought-resistant Crop***
Impact Measure	**Death**	**Damage**	**Death**	**Damage**	**Damage**
Domestic Shocks					
year t	0.504***	0.0705***	0.0188**	0.00694***	0.130**
	(0.151)	(0.0181)	(0.00859)	(0.00170)	(0.0660)
year t-1	0.344***	0.0647***	-0.00239	0.00388**	0.0276
	(0.121)	(0.0147)	(0.00758)	(0.00162)	(0.0496)
year t-2	0.503***	0.0711***	0.0548*	0.00121	0.107**
	(0.0687)	(0.0197)	(0.0310)	(0.00105)	(0.0504)
year t-3	0.363**	0.0396*	0.0382	0.000891	0.138**
	(0.158)	(0.0204)	(0.0450)	(0.00135)	(0.0651)
year t-4	-0.0129	0.0289	-0.00682	0.000469	0.0671**
	(0.0818)	(0.0209)	(0.0417)	(0.00122)	(0.0298)
year t-5	0.0794	0.0229*	0.0356	-0.000262	0.00694
	(0.0736)	(0.0118)	(0.0324)	(0.00104)	(0.0244)
year t-6	0.423***	0.0321***			
	(0.119)	(0.0106)			
year t-7	0.169**	-0.00575			
	(0.0708)	(0.0104)			
Cumulative effect	2.372***	0.324***	0.138	0.013***	0.477***
	(0.5640)	(0.1091)	(0.0902)	(0.0043)	(0.1542)
Foreign Shocks					
year t	0.0450	0.00568	0.00742	-0.00212*	-0.142
	(0.0578)	(0.00575)	(0.00741)	(0.00111)	(0.111)
year t-1	0.0980**	0.0264***	0.00402	0.00693***	-0.0540
	(0.0486)	(0.00639)	(0.00481)	(0.00199)	(0.0924)
year t-2	0.171***	0.0183***	-0.00285	-0.00412	-0.0701
	(0.0501)	(0.00634)	(0.00354)	(0.00652)	(0.0930)
year t-3	-0.0106	0.000237	-0.00371	-0.00474	0.105**
	(0.0798)	(0.00365)	(0.00448)	(0.00837)	(0.0490)
year t-4	-0.108*	0.000640	-0.00453	-0.00382	-0.00167
	(0.0589)	(0.00502)	(0.00456)	(0.00322)	(0.0363)
year t-5	0.0108	0.000496	-0.00907***	-0.00763***	0.0279
	(0.0332)	(0.00455)	(0.00166)	(0.00245)	(0.0255)

Continued Table 1-5

year t-6	0.106**	0.00280			
	(0.0445)	(0.00393)			
year t-7	-0.0678*	-0.0108*			
	(0.0386)	(0.00576)			
Cumulative effect	0.7977***	0.0438***	-0.0087	-0.0155	-0.1341
	(0.1940)	(0.0121)	(0.0079)	(0.0203)	(0.2931)
Log knowledge stocks (year t-1)	0.138	0.0800	0.885***	0.822***	-0.204
	(0.221)	(0.201)	(0.190)	(0.147)	(0.392)
Log GDP per capita	1.412	1.336	1.265	0.699	1.788
	(1.795)	(1.711)	(0.954)	(0.753)	(1.100)
Institution index	0.922	0.849	0.301	0.108	1.327
	(0.836)	(0.636)	(0.203)	(0.139)	(2.091)
Log Patent applications	1.143	1.128*	0.318	0.402	-0.513
	(0.802)	(0.640)	(0.290)	(0.346)	(0.450)
Observations	443	443	699	699	490
GMM criterion	0.2147	0.2468	0.1754	0.1726	0.0221
Number of countries	19	19	28	28	21
Timespan	1986-2009		1984-2009		1984-2009

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

Appendix

Appendix 1. Patent Search Codes

Our technology choices are driven in part by the need to avoid misclassification of technologies. For instance, while good data on hurricane impacts exist, we only consider their effect on innovation as one possible cause of increased flooding due to limitations in the IPC classification system. As shown below, we are able to identify patent classes pertaining to flood control. In contrast, while there are also clear patent classes for fortifying buildings from earthquakes, there are not clear patent classes for protecting patents from wind damage. Rather, these would appear as part of patent class E04H 9/14 (protection against "other dangerous influences, e.g. tornadoes, floods") or patent class E04H 9/16 (protection "against adverse conditions, e.g. extreme climate, pests"). Considering such patent classes would lead to irrelevant patents also being included. The list of patent classes or keyword searches used to classify each technology appears below.

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

E02B0030 Engineering work in connection with control or use of streams, rivers, coasts, or other marine sites (barrages or weirs E02B 7/00); Sealings or joints for engineering work in general.
E02B0031 Dams; Dykes; Sluice ways or other structures for dykes, dams, or the like (making embankments or dams in general E02D 17/18).
E02B007 - Barrages or weirs; Layout, construction, methods of, or devices for, making same (for protecting banks, coasts, or harbours E02B 3/04; sealings or joints.
E02B 3/16; handling building or like materials for hydraulic engineering E02D 15/00; foundations in general E02D 27/00).

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

Earthquake–proof building
((E04H 00902) <in> IC).
E04H 00902 - Buildings, groups of buildings, or shelters, adapted to withstand or provide protection against, abnormal external influences (e.g. war-like action, earthquake, extreme climate) withstanding earthquake or sinking of ground.

Appendix 2. Sample Countries for each type of technology

- ***Flood Control***

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

- ***Drought-resistant Crop***

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

- ***Quake-proof Building***

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

Appendix 3. Sensitivity to Lag Length

In the main paper, we include deaths and damages lagged through year t-5 for earthquakes and droughts, and lags of up to 7 years for floods. In this appendix we present the sensitivity analysis by gradually increasing the year lags. Most of our estimates are robust to the length of the lag, and the magnitude of coefficients for recent years does not change much as more distant lags are added to the model. The most sensitive result is quake-proof building in reaction to deaths, since the cumulative effect is only significant in the five-year distributed lag. While the contemporary effect remains similar across the various lags, as we add additional lags the coefficients for any one year become slightly smaller, with larger standard errors. We suspect this might be caused by multicollinearity issue, because many countries in our sample do not have any fatalities from earthquakes over the estimation period. In the damage model, where we have more non-zero observations, the cumulative effect is consistently significant and has less variation across different lag models, although the coefficients for certain individual years become insignificant in models with more lagged values.

Table 1-A3a: Flood Control (In reaction to deaths)

	(1)	(2)	(3)	(4)	(5)	(6)
year t	0.317**	0.323**	0.333**	0.542***	0.570***	0.636***
	(0.138)	(0.130)	(0.131)	(0.139)	(0.132)	(0.153)
year t-1	0.154***	0.229**	0.253***	0.385***	0.425***	0.477***
	(0.0521)	(0.0940)	(0.0862)	(0.0671)	(0.0693)	(0.0661)
year t-2	0.317**	0.379**	0.407**	0.508***	0.565***	0.624***
	(0.160)	(0.181)	(0.173)	(0.158)	(0.157)	(0.123)
year t-3	0.117	0.182	0.183	0.408*	0.497**	0.566***
	(0.143)	(0.179)	(0.173)	(0.237)	(0.223)	(0.196)
year t-4		-0.0420	-0.0439	0.119	0.185	0.252**
		(0.0602)	(0.0540)	(0.111)	(0.116)	(0.108)
year t-5			0.0756	0.163***	0.175***	0.233***
			(0.0479)	(0.0585)	(0.0582)	(0.0665)
year t-6				0.330**	0.370***	0.381***
				(0.157)	(0.138)	(0.120)
year t-7					0.188***	0.207***
					(0.0521)	(0.0638)
year t-8						0.0773
						(0.0596)
Cumulative effect	0.905***	1.070**	1.207***	2.455***	2.975***	3.453***
	(0.2817)	(0.4199)	(0.3774)	(0.7313)	(0.7682)	(0.6921)
Log knowledge stocks	0.408**	0.375*	0.349*	0.210	0.122	0.0403
(year t-1)	(0.182)	(0.208)	(0.201)	(0.248)	(0.249)	(0.244)
Log GDP per capita	1.973	0.642	1.120	1.754	2.816	3.474*
	(2.923)	(2.972)	(2.987)	(2.228)	(1.913)	(1.922)
Institution index	0.784	0.891	0.779	0.707	0.515	0.479
	(1.105)	(1.345)	(1.186)	(0.947)	(0.567)	(0.438)
Log Patent	0.182	0.757	0.695	1.225	1.198	1.294
applications	(1.120)	(1.246)	(1.211)	(1.014)	(0.911)	(0.875)
Number of obs.	443	443	443	443	443	443
GMM criterion	0.1920	0.2126	0.2141	0.1729	0.1762	0.1728
Number of countries	19	19	19	19	19	19

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

Table 1-A3b: Flood Control (In reaction to damage)

	(1)	(2)	(3)	(4)	(5)	(6)
year t	0.0590***	0.0658***	0.0685***	0.0810***	0.0814***	0.0712***
	(0.0151)	(0.0181)	(0.0179)	(0.0219)	(0.0234)	(0.0184)
year t-1	0.0437**	0.0511**	0.0506**	0.0473**	0.0465**	0.0420**
	(0.0210)	(0.0234)	(0.0212)	(0.0187)	(0.0206)	(0.0183)
year t-2	0.0336***	0.0371***	0.0278**	0.0532**	0.0550**	0.0403**
	(0.0119)	(0.0143)	(0.0123)	(0.0207)	(0.0239)	(0.0177)
year t-3	0.00364	0.00769	-0.00433	0.0490**	0.0467*	0.0374
	(0.00642)	(0.00864)	(0.00851)	(0.0226)	(0.0270)	(0.0230)
year t-4		0.00745	0.00909	0.0316*	0.0329	0.0214
		(0.0107)	(0.0112)	(0.0177)	(0.0233)	(0.0179)
year t-5			-0.0116*	0.0156**	0.0158	0.00455
			(0.00615)	(0.00731)	(0.0106)	(0.00752)
year t-6				0.0338***	0.0312**	0.0252**
				(0.0110)	(0.0146)	(0.0113)
year t-7					-0.00314	-0.00644
					(0.0110)	(0.00932)
year t-8						-0.0145**
						(0.00579)
Cumulative effect	0.140***	0.169**	0.140**	0.311***	0.306**	0.221**
	(0.0530)	(0.0689)	(0.0630)	(0.1157)	(0.1476)	(0.1110)
Log knowledge stocks (year t-1)	0.204	0.131	0.190	0.0268	0.0315	0.156
	(0.213)	(0.230)	(0.231)	(0.305)	(0.347)	(0.291)
Log GDP per capita	1.803	1.046	0.526	0.950	1.471	0.453
	(2.008)	(2.112)	(1.929)	(1.986)	(1.743)	(1.987)
Institution index	1.143	1.320	1.354	1.212	0.876	0.832
	(1.432)	(1.875)	(2.060)	(1.552)	(0.877)	(0.883)
Log Patent applications	0.476	0.884	0.949	1.264	1.109	1.143
	(0.894)	(0.963)	(0.886)	(0.953)	(0.955)	(0.924)
Number of obs.	443	443	443	443	443	443
GMM criterion	0.2113	0.2320	0.2333	0.1980	0.2148	0.2155
Number of countries	19	19	19	19	19	19

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

Table 1-A3c: Quake-proof Building (In reaction to death)

	(1)	(2)	(3)	(4)	(5)	(6)
year t	0.0116***	0.0119***	0.0116***	0.0115***	0.0118***	0.0103***
	(0.00242)	(0.00265)	(0.00275)	(0.00307)	(0.00334)	(0.00293)
year t-1	-0.00661*	-0.00590	-0.00627	-0.00591	-0.00571	-0.00883**
	(0.00362)	(0.00410)	(0.00447)	(0.00442)	(0.00426)	(0.00357)
year t-2	0.0567**	0.0610**	0.0626**	0.0451	0.0405	0.0285
	(0.0260)	(0.0290)	(0.0294)	(0.0357)	(0.0346)	(0.0339)
year t-3	0.00712	0.0129	0.0190	0.0130	0.00768	0.00523
	(0.0266)	(0.0280)	(0.0296)	(0.0335)	(0.0284)	(0.0257)
year t-4		0.0260	0.0303	0.0147	0.0110	-0.00418
		(0.0361)	(0.0374)	(0.0429)	(0.0424)	(0.0362)
year t-5			0.0644**	0.0497	0.0372	0.0390
			(0.0293)	(0.0313)	(0.0283)	(0.0294)
year t-6				-0.0814	-0.0936*	-0.101***
				(0.0587)	(0.0541)	(0.0382)
year t-7					-0.0480	-0.0459
					(0.0328)	(0.0498)
year t-8						-0.00364
						(0.0637)
Cumulative effect	0.069	0.106	0.182**	0.047	-0.039	-0.080
	(0.0463)	(0.0800)	(0.0896)	(0.1659)	(0.1361)	(0.0884)
Log knowledge stocks (year t-1)	0.889***	0.853***	0.914***	0.928***	0.946***	1.108***
	(0.150)	(0.165)	(0.188)	(0.187)	(0.155)	(0.119)
Log GDP per capita	0.775	0.792	0.803	0.617	0.445	0.641
	(1.014)	(0.980)	(0.879)	(0.972)	(0.995)	(1.103)
Institution index	0.174*	0.155*	0.258*	0.251*	0.234**	0.319**
	(0.0920)	(0.0847)	(0.145)	(0.128)	(0.111)	(0.161)
Log Patent applications	0.460*	0.460*	0.402*	0.490*	0.538**	0.454
	(0.273)	(0.267)	(0.218)	(0.257)	(0.274)	(0.287)
Number of obs.	699	699	699	699	699	699
GMM criterion	0.1523	0.1503	0.1550	0.1632	0.1628	0.1895
Number of countries	28	28	28	28	28	28

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

Table 1-A3d: Quake-proof Building (In reaction to damage)

	(1)	(2)	(3)	(4)	(5)	(6)
year t	0.0128***	0.0129***	0.0140***	0.0133***	0.0133***	0.0137***
	(0.00155)	(0.00148)	(0.00172)	(0.00148)	(0.00163)	(0.00178)
year t-1	0.00162	0.00189	0.00264	0.00201	0.00190	0.00119
	(0.00157)	(0.00164)	(0.00208)	(0.00209)	(0.00196)	(0.00207)
year t-2	0.00200	0.00241*	0.00290*	0.00205	0.00186	0.00114
	(0.00122)	(0.00140)	(0.00158)	(0.00166)	(0.00153)	(0.00161)
year t-3	0.000794	0.00132	0.00175*	0.00137	0.00111	0.000841
	(0.000987)	(0.00102)	(0.000931)	(0.00117)	(0.00124)	(0.00104)
year t-4		0.00171	0.00274**	0.00184	0.00160	0.00130
		(0.00114)	(0.00131)	(0.00159)	(0.00171)	(0.00171)
year t-5			0.00367***	0.00231*	0.00181	0.00183
			(0.00111)	(0.00139)	(0.00172)	(0.00195)
year t-6				-0.00265	-0.00323	-0.00334*
				(0.00211)	(0.00223)	(0.00183)
year t-7					-0.00152	-0.00135
					(0.000983)	(0.00130)
year t-8						0.000330
						(0.00177)
Cumulative effect	0.017***	0.020***	0.028***	0.020**	0.017**	0.016***
	(0.0041)	(0.0046)	(0.0049)	(0.0082)	(0.0084)	(0.0053)
Log knowledge stocks (year t-1)	0.712***	0.698***	0.796***	0.793***	0.826***	1.014***
	(0.177)	(0.199)	(0.229)	(0.252)	(0.228)	(0.218)
Log GDP per capita	-0.327	-0.220	-0.375	-0.368	-0.592	-0.707
	(0.989)	(0.974)	(0.590)	(0.852)	(0.899)	(0.632)
Institution index	0.158	0.149	0.365	0.239	0.251*	0.433**
	(0.142)	(0.144)	(0.241)	(0.151)	(0.138)	(0.219)
Log Patent applications	0.663*	0.613*	0.498**	0.589*	0.663*	0.596**
	(0.366)	(0.343)	(0.204)	(0.310)	(0.339)	(0.268)
Number of obs.	699	699	699	699	699	699
GMM criterion	0.1555	0.1503	0.1555	0.1611	0.1596	0.2027
Number of countries	28	28	28	28	28	28

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

Table 1-A3e: Drought-resistant Crop (In reaction to damage)

	(1)	(2)	(3)	(4)	(5)
year t	0.0754**	0.0754*	0.0954*	0.0997*	0.102*
	(0.0378)	(0.0396)	(0.0559)	(0.0521)	(0.0556)
year t-1	0.0126	0.00887	0.0201	0.0163	0.0158
	(0.0339)	(0.0387)	(0.0437)	(0.0392)	(0.0383)
year t-2	0.0729*	0.0640	0.0996**	0.0877	0.0923*
	(0.0440)	(0.0426)	(0.0492)	(0.0561)	(0.0554)
year t-3	0.0798	0.0733	0.122*	0.125*	0.131*
	(0.0705)	(0.0635)	(0.0738)	(0.0698)	(0.0699)
year t-4		0.00626	0.0680**	0.0697**	0.0717**
		(0.0100)	(0.0335)	(0.0306)	(0.0343)
year t-5			-0.0192	-0.0239	-0.0270
			(0.0393)	(0.0420)	(0.0449)
year t-6				-0.0511	-0.0457
				(0.0725)	(0.0744)
year t-7					0.00508
					(0.0355)
Cumulative effect	0.241**	0.228*	0.385***	0.324***	0.345**
	(0.1161)	(0.1190)	(0.1259)	(0.1169)	(0.1427)
Log knowledge stocks	0.596***	0.564***	0.135	0.0869	0.0813
(year t-1)	(0.171)	(0.177)	(0.466)	(0.525)	(0.504)
Log GDP per capita	1.729	1.836	1.999*	1.738	1.831
	(1.309)	(1.218)	(1.209)	(1.300)	(1.230)
Institution index	-0.152	-0.145	0.680	1.061	1.425
	(0.109)	(0.114)	(1.515)	(2.241)	(3.328)
Log Patent	-0.522	-0.542	-0.557	-0.498	-0.533
applications	(0.541)	(0.530)	(0.534)	(0.498)	(0.474)
Number of obs.	490	490	490	490	490
GMM criterion	0.0398	0.0404	0.0261	0.0239	0.0232
Number of countries	21	21	21	21	21

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

Appendix 4. Lag sensitivity without knowledge stocks (no instrumental variables)

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:

$$PAT_{jit} = f(\sum_{l=0}^{L} \beta_l D_{i,t-l}, \beta_H \sum_{h=L+1}^{H} D_{i,t-h}, \ \beta_X X_{it}, \ \eta_i, \theta_t) \quad \text{(A1)}$$

For example, if L = 3, the model includes a separate damage coefficient for years 0 to t-3, and a single coefficient, β_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. X_{it} represents a matrix of the various control variables used. Country fixed effects and year fixed effects are also included in the model. By not instrumenting for impacts, these models also allow us to confirm the expected bias from potential endogeneity discussed in the body of the paper.

Table 4A through Table 4E present the results by technologies. The tables show our results are robust to various lag lengths. The AIC and BIC values generally indicate out choice of the distributed lag length (for different types of technologies) picks up the best fit of a model. Moreover, in most cases, the coefficient on the sum of past events is insignificant (particularly with the increase of year lags), suggesting that additional lags are unimportant. In the flood control case (in reaction to damages), the coefficient on the sum of past damages is negative and significant at the ten percent level, which may suggest the earlier events may already affect the adaptive capacity and thus reduce the need for today's innovations. This is consistent with the insignificant coefficient on knowledge stocks discussed in the text. Finally, without instrumenting for disaster damages, we find that the sum of the various β_j coefficients, are much lower compared to the sum in Table 4 in the case of flood control and drought.

Table 1-A4a Flood control (in reaction to deaths)

Lags	(3)	(4)	(5)	(6)	(7)	(8)
year t	0.155**	0.158**	0.163**	0.204**	0.189**	0.191**
	(0.0664)	(0.0731)	(0.0753)	(0.0916)	(0.0848)	(0.0855)
year t-1	0.0644	0.0649	0.0849**	0.104**	0.131***	0.122***
	(0.0479)	(0.0473)	(0.0423)	(0.0420)	(0.0425)	(0.0432)
year t-2	0.280***	0.272**	0.278***	0.301***	0.314***	0.321***
	(0.0920)	(0.108)	(0.106)	(0.0952)	(0.0904)	(0.0863)
year t-3	0.143**	0.143**	0.103	0.119*	0.146**	0.150**
	(0.0643)	(0.0643)	(0.0734)	(0.0709)	(0.0619)	(0.0599)
year t-4		-0.0216	-0.0248	-0.0669*	-0.0676*	-0.0581
		(0.0443)	(0.0438)	(0.0382)	(0.0363)	(0.0383)
year t-5			0.0444	0.0479	-0.00798	-0.00976
			(0.0544)	(0.0559)	(0.0386)	(0.0385)
year t-6				0.0756*	0.0841*	0.0549
				(0.0452)	(0.0484)	(0.0395)
year t-7					0.0534	0.0500
					(0.0525)	(0.0500)
year t-8						-0.0218
						(0.0463)
Cumulative effect	0.643***	0.617***	0.649***	0.784***	0.842***	0.799***
	(0.1581)	(0.1458)	(0.1411)	(0.1639)	(0.1666)	(0.1623)
Sum of past deaths	-0.0383	-0.0399	-0.0486	-0.0612	-0.0708*	-0.0789*
	(0.0378)	(0.0393)	(0.0397)	(0.0375)	(0.0374)	(0.0420)
Log GDP per capita	2.119**	2.142**	2.284**	2.451***	2.558***	2.648**
	(0.906)	(0.928)	(0.952)	(0.951)	(0.963)	(1.037)
Institution index	0.208	0.207	0.207	0.209	0.215	0.216*
	(0.146)	(0.144)	(0.141)	(0.134)	(0.132)	(0.130)
Log Patent applications	0.439	0.447	0.480	0.576	0.628*	0.654*
	(0.362)	(0.362)	(0.358)	(0.355)	(0.347)	(0.338)
Number of obs.	443	443	443	443	443	443
AIC	1295.392	1297.327	1297.401	1294.587	1292.818	1293.933
BIC	1422.292	1428.321	1432.489	1433.769	1436.093	1441.302

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

Table 1-A4b Flood control (in reaction to damages)

Lags	(3)	(4)	(5)	(6)	(7)	(8)
year t	0.0443***	0.0449***	0.0432***	0.0476***	0.0479***	0.0479***
	(0.0133)	(0.0134)	(0.0135)	(0.0128)	(0.0134)	(0.0132)
year t-1	0.0373**	0.0393**	0.0393**	0.0369**	0.0365**	0.0370**
	(0.0156)	(0.0158)	(0.0161)	(0.0179)	(0.0167)	(0.0166)
year t-2	0.0264***	0.0261***	0.0271***	0.0283**	0.0288**	0.0280**
	(0.00938)	(0.00979)	(0.0100)	(0.0114)	(0.0128)	(0.0119)
year t-3	0.00412	0.00468	0.00501	0.00911	0.00911	0.0101
	(0.0102)	(0.0108)	(0.0108)	(0.0115)	(0.0114)	(0.0128)
year t-4		0.00444	0.00419	0.00476	0.00468	0.00472
		(0.00794)	(0.00811)	(0.00847)	(0.00819)	(0.00799)
year t-5			-0.00281	-0.00227	-0.00189	-0.00199
			(0.00437)	(0.00486)	(0.00554)	(0.00545)
year t-6				0.00221	0.00237	0.00302
				(0.00583)	(0.00614)	(0.00689)
year t-7					-0.0136**	-0.0129***
					(0.00624)	(0.00493)
year t-8						-0.0142**
						(0.00709)
Cumulative effect	0.112***	0.119**	0.116**	0.127**	0.114*	0.102
	(0.0432)	(0.0521)	(0.0571)	(0.0632)	(0.0634)	(0.0662)
Sum of past damages	-0.00709	-0.00825*	-0.00951**	-0.0119**	-0.0115**	-0.0108*
	(0.00521)	(0.00466)	(0.00475)	(0.00480)	(0.00582)	(0.00636)
Log GDP per capita	1.979**	2.042**	2.116***	2.146***	2.126***	2.089**
	(0.854)	(0.817)	(0.800)	(0.764)	(0.823)	(0.902)
Institution index	0.223*	0.222*	0.222*	0.228*	0.227*	0.226*
	(0.133)	(0.128)	(0.126)	(0.120)	(0.122)	(0.123)
Log Patent applications	0.574*	0.632**	0.661**	0.763**	0.754**	0.745***
	(0.310)	(0.309)	(0.309)	(0.310)	(0.296)	(0.288)
						(0.00636)
Number of obs.	443	443	443	443	443	443
AIC	1252.81	1251.582	1252.516	1249.781	1251.691	1253.445
BIC	1379.711	1382.577	1387.603	1388.962	1394.966	1400.814

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

Table 1-A4c Quake-proof Building (in reaction to deaths)

Lags	(3)	(4)	(5)	(6)	(7)	(8)
year t	0.0145**	0.0148**	0.0149**	0.0149**	0.0149**	0.0149**
	(0.00640)	(0.00633)	(0.00613)	(0.00614)	(0.00609)	(0.00603)
year t-1	0.00675	0.00715	0.00783	0.00783	0.00787	0.00790
	(0.00813)	(0.00801)	(0.00770)	(0.00769)	(0.00762)	(0.00751)
year t-2	0.0827**	0.0821**	0.0816**	0.0815**	0.0814**	0.0813**
	(0.0384)	(0.0383)	(0.0382)	(0.0382)	(0.0380)	(0.0379)
year t-3	0.154***	0.154***	0.153***	0.153***	0.152***	0.152***
	(0.0395)	(0.0393)	(0.0394)	(0.0394)	(0.0396)	(0.0398)
year t-4		0.0721*	0.0709*	0.0709*	0.0707*	0.0703*
		(0.0374)	(0.0376)	(0.0375)	(0.0375)	(0.0376)
year t-5			0.119***	0.119***	0.118***	0.118***
			(0.0264)	(0.0264)	(0.0264)	(0.0263)
year t-6				0.0127	0.0125	0.0119
				(0.0398)	(0.0401)	(0.0409)
year t-7					0.0212	0.0208
					(0.0335)	(0.0332)
year t-8						0.0287
						(0.0475)
Cumulative effect	0.258***	0.330***	0.446***	0.459***	0.479***	0.506***
	(0.0533)	(0.0845)	(0.0975)	(0.1283)	(0.1513)	(0.1777)
Sum of past deaths	0.0323	0.0252	0.0104	0.00996	0.00787	0.00382
	(0.0345)	(0.0365)	(0.0400)	(0.0416)	(0.0483)	(0.0549)
Log GDP per capita	1.607	1.574	1.507	1.505	1.503	1.493
	(1.056)	(1.032)	(0.987)	(0.991)	(0.989)	(0.981)
Institution index	0.0403	0.0391	0.0378	0.0378	0.0377	0.0376
	(0.0702)	(0.0697)	(0.0692)	(0.0691)	(0.0689)	(0.0688)
Log Patent applications	0.532**	0.516**	0.490*	0.489*	0.485**	0.480**
	(0.264)	(0.260)	(0.253)	(0.251)	(0.242)	(0.233)
Number of obs.	699	699	699	699	699	699
AIC	2115.289	2114.141	2102.199	2104.189	2105.958	2107.164
BIC	2265.427	2268.829	2261.437	2267.976	2274.296	2280.051

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

Table 1-A4d Quake-proof Building (in reaction to damages)

Lags	(3)	(4)	(5)	(6)	(7)	(8)
year t	0.00506*	0.00511*	0.00521*	0.00521*	0.00521*	0.00521*
	(0.00300)	(0.00302)	(0.00304)	(0.00305)	(0.00306)	(0.00303)
year t-1	0.00378***	0.00384***	0.00398***	0.00399***	0.00400***	0.00401***
	(0.00122)	(0.00122)	(0.00123)	(0.00124)	(0.00124)	(0.00125)
year t-2	0.00425***	0.00426***	0.00430***	0.00430***	0.00430***	0.00430***
	(0.00136)	(0.00136)	(0.00135)	(0.00136)	(0.00136)	(0.00135)
year t-3	0.00629***	0.00641***	0.00641***	0.00641***	0.00641***	0.00641***
	(0.000972)	(0.00101)	(0.00103)	(0.00103)	(0.00103)	(0.00103)
year t-4		0.00414***	0.00438***	0.00438***	0.00438***	0.00436***
		(0.00148)	(0.00148)	(0.00148)	(0.00148)	(0.00148)
year t-5			0.00546***	0.00546***	0.00546***	0.00544***
			(0.00108)	(0.00110)	(0.00109)	(0.00108)
year t-6				0.00226	0.00228	0.00225
				(0.00157)	(0.00155)	(0.00157)
year t-7					0.00239*	0.00244**
					(0.00124)	(0.00122)
year t-8						0.00305**
						(0.00154)
Cumulative effect	0.019***	0.024***	0.030***	0.032***	0.034***	0.037***
	(0.0047)	(0.0058)	(0.0066)	(0.0077)	(0.0086)	(0.0096)
Sum of past damages	0.00285**	0.00262**	0.00215	0.00213	0.00207	0.00185
	(0.00124)	(0.00127)	(0.00136)	(0.00137)	(0.00155)	(0.00176)
Log GDP per capita	1.693**	1.645**	1.534*	1.530*	1.523*	1.493*
	(0.843)	(0.830)	(0.813)	(0.824)	(0.837)	(0.848)
Institution index	0.0554	0.0532	0.0513	0.0512	0.0510	0.0504
	(0.0649)	(0.0641)	(0.0635)	(0.0633)	(0.0630)	(0.0624)
Log Patent applications	0.623**	0.616**	0.607**	0.607**	0.604**	0.598**
	(0.254)	(0.251)	(0.248)	(0.246)	(0.240)	(0.234)
Number of obs.	699	699	699	699	699	699
AIC	2130.367	2129.542	2119.952	2121.932	2123.816	2124.201
BIC	2280.506	2284.23	2279.19	2285.719	2292.153	2297.088

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

Table 1-A4e Drought-resistant crop (in reaction to damages)

Lags	(3)	(4)	(5)	(6)	(7)	(8)
year t	0.0665***	0.0646***	0.0605***	0.0613***	0.0594***	0.0580***
	(0.00900)	(0.00922)	(0.00963)	(0.0116)	(0.0122)	(0.0119)
year t-1	0.0158	0.0130	0.0113	0.0115	0.00919	0.00861
	(0.0250)	(0.0266)	(0.0270)	(0.0277)	(0.0287)	(0.0289)
year t-2	0.0539**	0.0513**	0.0455*	0.0459*	0.0442	0.0380
	(0.0247)	(0.0252)	(0.0262)	(0.0272)	(0.0279)	(0.0280)
year t-3	0.0102	0.00785	0.000994	0.00163	-0.000858	-0.00484
	(0.0129)	(0.0130)	(0.0141)	(0.0159)	(0.0167)	(0.0174)
year t-4		0.0218	0.0174	0.0180	0.0160	0.0118
		(0.0229)	(0.0238)	(0.0250)	(0.0251)	(0.0247)
year t-5			0.0271	0.0275	0.0251	0.0209
			(0.0231)	(0.0245)	(0.0248)	(0.0241)
year t-6				-0.00934	-0.0118	-0.0183
				(0.0275)	(0.0266)	(0.0253)
year t-7					-0.00250	-0.00907
					(0.0355)	(0.0332)
year t-8						0.00152
						(0.0364)
Cumulative effect	0.146**	0.159*	0.163	0.157	0.139	0.107
	(0.0616)	(0.0842)	(0.1112)	(0.1440)	(0.1788)	(0.2086)
sum of past damages	0.00967	0.00500	-0.00774	-0.00646	-0.0129	-0.0301
	(0.0264)	(0.0284)	(0.0317)	(0.0364)	(0.0367)	(0.0345)
Log GDP per capita	0.428	0.413	0.372	0.362	0.409	0.523
	(0.700)	(0.696)	(0.678)	(0.703)	(0.722)	(0.731)
Institution index	0.0698	0.0680	0.0595	0.0599	0.0573	0.0526
	(0.144)	(0.141)	(0.132)	(0.133)	(0.129)	(0.121)
Log Patent applications	0.0950	0.127	0.217	0.213	0.234	0.299
	(0.256)	(0.259)	(0.253)	(0.253)	(0.248)	(0.237)
Number of obs.	495	495	495	495	495	495
AIC	1244.396	1245.435	1242.889	1244.859	1246.421	1244.043
BIC	1383.146	1388.39	1390.048	1396.223	1401.989	1403.816

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

Appendix 5. Instrument Quality

To assess the quality of our instruments, Table 1-A5 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 inter-correlations among instruments. If the Shea partial R^2 is significantly smaller than the standard partial R^2, it suggests there are not enough unique instruments to identify each endogenous variable. As we see in Table 1-A5, that is not the case, as both partial R^2 values are similar for each variable.

Table 1-A5 Instrumental Variables Test

	Flood Control		*Quake-proof Building*		*Drought-Resistant Crops*	
	partial R2	Shea partial R2	partial R2	Shea partial R2	partial R2	Shea partial R2
Deaths(t)	0.4498	0.365	0.4739	0.4316		
Deaths(t-1)	0.445	0.3813	0.4668	0.438		
Deaths(t-2)	0.4193	0.4166	0.2756	0.2687		
Deaths(t-3)	0.3997	0.4292	0.2977	0.2859		
Deaths(t-4)	0.4048	0.3997	0.2957	0.2864		
Deaths(t-5)	0.4052	0.399	0.3073	0.2761		
Deaths(t-6)	0.3546	0.3129				
Deaths(t-7)	0.3778	0.3402				
Knowledge Stock (t-1)	0.3092	0.3015	0.2117	0.211		
Damages(t)	0.3616	0.3092	0.4033	0.3849	0.1187	0.1086
Damages(t-1)	0.3465	0.3105	0.3924	0.3752	0.1101	0.1011
Damages(t-2)	0.3449	0.2991	0.3185	0.3053	0.1112	0.1057
Damages(t-3)	0.3474	0.328	0.3352	0.3193	0.1214	0.1187
Damages(t-4)	0.3489	0.3388	0.3243	0.3165	0.1193	0.1144
Damages(t-5)	0.3545	0.34	0.346	0.3259	0.1017	0.0884
Damages(t-6)	0.3519	0.3178				
Damages(t-7)	0.3393	0.298				
Knowledge Stock (t-1)	0.3092	0.3045	0.2117	0.2027	0.1336	0.1322

Appendix References

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Chapter 2: Technological Innovation, Social Learning and Natural Hazard Mitigation: Evidence on Earthquake Losses

1. Introduction

A natural disaster occurs when hazard meets vulnerability. Although most disasters are triggered by exogenous natural shocks, the actual impact of these events also depends on the capacity of human societies to effectively prepare for and cope with disaster risks (Cutter et al., 2003; Schwab et al., 2007). Why some communities suffer higher losses and what affects their ability to deal with environmental hazards are important questions in the economics of natural disasters. To date, the empirical literature has focused mainly on two factors, income and institutions, and provided consistent evidence that countries with higher income and better institutions suffer fewer fatalities from natural disasters (e.g., Kahn, 2005; Anbarci et al., 2005; Escaleras et al., 2007; Toya and Skidmore, 2007; Kellenberg and Mobarak, 2008; Keefer et al., 2011; Ferreira et al., 2013; Rashky, 2008; Mendelsohn and Saher, 2011). The underlying argument is that these countries generally have better infrastructure and preventive technologies, and tend to adopt more effective regulations, emergency response systems, as well as other precautionary measures, that lead to better protection against natural disasters.

While the existing literature mostly focuses on the aggregated effects of socioeconomic conditions on disaster losses, research on more disaggregated mechanisms of disaster mitigation and the dynamics of societal adaptation to natural hazards is lacking. Given the recurrent nature of most natural disasters, it is crucial for both researchers and policy makers to think about whether people are constantly learning from disasters, how they acquire and accumulate knowledge to cope with recurrent natural shocks and how effective their knowledge is in mitigating future disaster risks. This research extends the line of natural hazards literature by exploring these questions, and furthermore, connects it with a larger emerging literature on adaptation to natural disasters and climate change. It elucidates the role of knowledge in adaptive capacity by linking it with social learning and evaluating its effectiveness in disaster mitigation.

Specifically, in this paper I focus on earthquakes and consider two forms of knowledge that are relevant for mitigating earthquake impacts: 1) formal/technical knowledge (innovation), which is measured by the accumulation of patents in earthquake-proof building technologies in a country; and 2) informal knowledge, which is measured by a country's prior earthquake experiences, since conventional wisdom holds that past disaster events often enhance people's hazard awareness and motivate them to undertake or improve protective measures. My central prediction is that countries with more quake-proof building innovations and greater earthquake exposure in the past are better adapted to earthquakes, and would therefore suffer fewer losses.

One unique contribution of this research is using patent data to empirically examine the role of technological innovation in disaster risk mitigation. Although the importance of science and technology development for disaster management has been widely recognized in the policy world (e.g., United Nations International Strategy for Disaster Reduction, 2009), there is little empirical research delving into this issue. I argue that the development of risk-mitigating technologies deserves special attention for two reasons. First, income and institutions can conceivably affect disaster impacts through multiple channels. While most recent studies have investigated the aggregated effects, it becomes increasingly important to disentangle these operating channels for us to better understand what contributes to adaptive capacity and inform disaster mitigation policy making. Second, innovation produces new knowledge that serves as a public good in the sense that it can be adopted by non-inventors and yields substantial social benefits at home and abroad. In the global context, while a vast majority of the R&D activities are performed by industrialized countries (National Science Board, 2010), the developing world can potentially exploit the risk-mitigating knowledge produced by their developed counterparts. Therefore, I also investigate the possible effect of foreign technical knowledge on reducing earthquake losses.

However, examining technical innovations alone would raise endogeneity concerns because the risk-mitigating innovations could be induced by recent disaster impacts, as suggested in Miao and Popp (2014). To address this issue, I include prior earthquake experience, considering it as not only a driver of social learning, but also a proxy for informal knowledge of coping with subsequent earthquakes. Some recent studies have also examined the link between the general hazard exposure and actual disaster losses, assuming that countries or communities exposed to relatively greater hazard risks are better able to prevent losses (e.g., Anbarci et al., 2005; Escaleras et al., 2007; Keefer et al., 2011; Schumacher and Strobl, 2011; Hsiang and Narita, 2012; Sadowski and Sutter, 2008; Neumayer et al. 2014). However, most of them treat hazard exposure/propensity as a country-specific, time-constant characteristic by measuring the frequency and intensity of experiencing natural hazards over a certain period of time. I take a different approach in this study by conceptualizing the prior disasters as the motivation for learning and creating a weighted experience stock, assuming that the influence of earlier events may wear off over time and people are more responsive to the most recent shocks.

Another contribution of this paper is to address the issue of missing data on disaster losses, which is a serious problem for widely-used disaster databases, including the Emergency Events Database (EM-DAT), but has not yet been addressed or even acknowledged in the empirical literature. The earthquake data used in this paper are drawn from the National Geophysical Data Center's (NGDC) Significant Earthquake Database, because it provides more details on earthquake physics than the EM-DAT does. Similar to the EM-DAT, a considerable proportion of the events in the NGDC database have missing values on earthquake-related deaths and damages. Therefore, I used multiple estimation strategies to address the missing data issue and obtained consistent results across different models.

My empirical analysis uses a global cross section of 894 earthquake events in 79 countries between1980 and 2010. To preview the paper's results, both technical knowledge stocks and past accumulated earthquake experiences play an important role in reducing a country's fatalities from large earthquakes, controlling for the physical quake magnitude and other relevant national attributes. The effect of prior experiences on risk reduction is more pronounced in developed countries, while this influence largely operates through the mechanism of technological development. I did not find strong evidence on the effects of knowledge spillovers on reducing earthquake losses. Overall, my findings highlight the importance of incorporating technological innovation as part of a long-term natural hazard mitigation policy, and also suggest the need for more policy efforts at the international level to facilitate the diffusion and transfer of risk-mitigating technologies across countries.

The remainder of this paper is organized as follows. Section 2 discusses the relevant literature. Section 3 presents my conceptual model, followed by Section 4, which describes the data and the estimation strategies. Section 5 presents the main estimation results and Section 6 concludes.

2. Relevant literature

This paper is part of a growing literature on the determinants of disaster impacts (for a review of the recent literature, see Kousky, 2013), and my distinctive focus on the role of social learning and innovation naturally brings together separate strands of research on natural disasters, climate adaptation and technology spillovers. As discussed earlier, the empirical literature on disaster damages has traditionally focused on the role of income and institutions in determining natural disaster deaths and damages, with institutions often being examined through various lenses including democracy (Kahn, 2005; Keefer et al., 2011), public sector corruption (Escaleras et al., 2006), inequality (Anbarci et al., 2005), and governance (Ferreira et al., 2013). Very few studies have looked into the link between natural disasters and technological change. One exception is Alan Barreca et al. (2012), which examines how the adoption of residential air conditioning reduces mortalities from extreme hot weather in the United States. This paper further extends this line of research by using a cross-country sample and focusing more specifically on the mitigating effect of technological innovation. My study also draws upon Miao and Popp (2014), who examine the impact of three types of natural disasters, including floods, droughts, and earthquakes on the innovation of their relevant mitigating technologies and finds consistent evidence that recent disaster shocks spur technical innovations. While the aforementioned paper suggests the private sector adapts to natural hazards by innovating, this paper takes a further step by asking whether these innovations lead to significant reductions in current disaster losses.

While the literature is largely silent on the effect of technical knowledge, several recent studies have examined long-term disaster exposure/propensity as one of the determinants of disaster losses, hypothesizing that countries at higher levels of risk are better prepared for the relevant disasters. For example, Anbarci et al. (2005) and Escaleras et al. (2007) measure earthquake exposure by calculating the number of 6+ Richter scale quakes that a country has experienced over a relatively long period, with only the latter providing modest evidence on an inverse relationship between exposure and fatalities. Keefer et al. (2011) take a slightly different approach by using the sum of physical strength (explosive equivalent) of large earthquakes that occurred between 1960 and 2008 as a proxy for a country's earthquake propensity. They show that not only countries more prone to earthquakes suffer fewer fatalities but also the reduction effect of earthquake propensity is larger in developed and less corrupt nations. In another study, Neumayer et al. (2014) examine the impact of disaster propensity (defined as the expected frequency and magnitude of hazards) in the cases of earthquakes, tropical cyclones and floods using a global sample. Using a quantile regression, they find that a country's disaster propensity has more pronounced effects in reducing economic losses of larger events (in the upper quantile of the damage function). Despite their similar focus on disaster exposure and adaptation, these studies differ in their interpretation of the mechanism that exposure affects damages. While the first two studies frame the effect of long-term exposure as "learning-by-doing," the latter two argues that exposure affects the political incentive of government investment in disaster mitigation, thereby causing heterogeneous responses across different groups of nations and events of different scales.[28]

The evidence on adaptation motivated by disaster exposure has also been found in studies concerning other types of natural hazards. Hsiang and Narita (2012) examine adaptation to tropical cyclones (TC) at the global scale by using the average of maximum wind speed and energy dissipated of TCs a country has experienced over the study period to measure its climatological TC exposure. They find that countries that are more exposed to TC climate suffer slightly lower marginal losses from a storm. Sadowski and Sutter (2008), in another study modeling damages from tropical cycles within the United States, find that a prior hurricane that occurred ten or more years earlier can significantly reduce current damages by presumably motivating disaster mitigation efforts. What distinguishes their study from most other research is their investigation of

[28] To refute the explanation proposed in earlier research, Keefer et al. (2011) argue that the effect of earthquake exposure would be independent of the income and political characteristics of countries, if learning-by-doing is costless. However, it seems difficult to rule out the possibility of social learning for this reason, because one could argue that high-income or more democratic countries have stronger learning capacity and thus, can more effectively translate their prior disaster experiences into knowledge for coping with future disasters.

more than 60 definitions of a past hurricane to explore which type of events result in significant reductions in subsequent hurricane damages. Finally, Schumacher and Strobl (2011) examine how disaster exposure affects the relationship between income and disaster losses in a multi-hazard setting, arguing that countries with greater exposure are likely to experience first decreasing losses and then increasing ones with higher income level while the pattern is reversed for less exposed countries. To measure hazard-specific exposure, their study uses a global gridded spatial disaster risk dataset that measure natural hazard risks and local population exposure.[29]

To explore the potential role of global knowledge stocks in disaster risk reduction, this research draws on another strand of literature on knowledge spillovers. The notion is that technological innovation is a public good (i.e., non-rivalry and non-excludable), meaning that the knowledge embodied in new technologies can be accessed and adopted by non-inventors, thereby generating substantial social benefits (Stephan, 2011). Most empirical studies in this field focus on knowledge spillovers in the global context and mainly examine two issues: the effect of technology spillovers on economic development and productivity growth, as well as the mechanism of knowledge spillovers (for a review of this literature, see Keller, 2001). My research adds to this literature by using disaster damages as a new outcome measure and examining the differential effects of foreign knowledge stocks across countries.

3. Conceptual model

To understand how societies acquire knowledge from their past disaster experiences to mitigate future hazard risks, I draw on the prior literature and begin with a disaster damage model in which the losses from a natural disaster (L) are a function of the physical intensity of the disaster (M) and

[29] Specifically, they use the natural disaster global hot-spots data developed jointly by the World Bank Hazard Management Unit and the Center for Hazards and Risk Research Unit at Columbia University.

the characteristics of the affected countries reflecting local population exposure to the hazard (*POP*) and their capacity to respond to the shock (*C*). The model is consistent with the conventional wisdom that adaptive capacity is socially determined and place based, which leads to differential disaster impacts across communities, even if they are hit by natural shocks of the same strength (Kousky, 2013).

$$L = f_1 (M, POP, C) \tag{1}$$

The key innovation of this model is conceptualizing knowledge as an important component of adaptive capacity, which includes both formal technical knowledge (*TK*), as measured by patented innovations, and informal knowledge (*IK*) of coping with disasters. It is important to note that while formal knowledge is often developed by experts (e.g., seismic engineers in the case of earthquake), informal knowledge could be laymen's understanding of specific natural hazards (e.g., causes and potential consequences, probability of occurrence) and how to prepare for and respond to the specific hazard.[30] This type of knowledge is not directly observed and thus, measured by prior disaster experiences (*EXP*), as the disaster and climate change literatures widely suggest that recent shocks or weather fluctuations provide new information to update people's risk perception and awareness of the hazards (e.g., Gallagher, 2014; Deryugina, 2013). Another reason for considering how disaster experiences affect laymen knowledge is that for most of them, the efficacy of disaster-mitigating measures (e.g., quake-proof buildings) is unknown until a disaster occurs (Neumayer et al., 2013). Hence, they tend to have a better idea about disaster-proofing after experiencing an event. Note that the generation of disaster-specific knowledge, both formal and informal, is not only motivated by prior disaster experiences but also influenced by a country's

[30] The laymen knowledge is not necessarily the "correct" answers to factual questions but involves heuristics that people use to process information and make decisions. (Johnson, 1992)

income (Y) and institutions (I).[31]

$$TK = f_2\,(EXP,\ Y,\ I) \tag{2}$$

$$IK = f_3\,(EXP,\ Y,\ I) \tag{3}$$

I then model a country's adaptive capacity (C) as a function of its knowledge (TK, IK), income (Y), institutions (I), and other relevant socioeconomic characteristics (X) that may influence its ability to prepare for and respond to natural disasters.

$$C = f_4\,(TK,\ IK,\ Y,\ I,\ X) \tag{4}$$

Combining all the equations above to remove the unobserved informal knowledge and adaptive capacity provides the following relationship:

$$L = f_5\,(M,\ POP,\ TK,\ EXP,\ Y,\ I,\ X) \tag{5}$$

In this final model, I posit that a country that has accumulated more technical knowledge in disaster reduction and more prior disaster experiences would suffer fewer losses from the current shocks. Because the capacity to generate knowledge usually varies across countries depending on their socioeconomic conditions, it is particularly important to account for other national attributes that may simultaneously affect learning and disaster losses in the model to avoid omitted variable bias. Also note that this conceptual model focuses on a closed economy and does not include foreign technical knowledge, though the investigation of foreign knowledge is discussed in the results section.

4. Data and models

[31] By institutions, I refer not only to the national political regime and social inequality but also to institutions specifically related to science and technology development, such as a country's patent system.

The data used in this research are collected from a variety of sources to measure technical knowledge, earthquake-related losses and past experiences, and country characteristics. I discuss the earthquake data last, given that the nature of the data directly affects my estimation strategies.

4.1 Patent data and technical knowledge

To construct the variable for technical knowledge, I use the data on patents filed in the earthquake-proof building technology from an online global patent database, *Delphion.com*. These patents are identified based on the International Patent Code (IPC). A majority of the identified patents are for seismic and structural engineering technologies such as damper device, vibration absorber, quake-immune curtain wall system, and building collapse control systems. Appendix 1 provides more details on my search strategy. Considering the fact that inventors can patent the same innovation in multiple countries where they desire protection, I count multiple patents representing the same invention only once in the sample, and assign it to only one country where the first inventor is located according to the patent document.[32] Although patents are a common and direct measure for tracking technological innovation in the literature, it should be noted that it is far from a perfect measure because first, not all inventions get patented, and second, the number of patent applications is heavily influenced by a country's patent system.[33] In this study, I am less concerned about the first issue because in the model I include past disaster experience as a proxy for informal

[32] I take this approach mainly because in this research I make a distinction between the knowledge (patents) produced by one country and knowledge produced abroad. Therefore, if a U.S. inventor has patented an invention in both the U.S. and Japan, it is considered as the domestic knowledge owned by the United States and foreign knowledge external to Japan.

[33] It should be noted that patent data seem the only choice available in this research given my focus on a specific type of technology, and data on other alternative measures, such as R&D expenditure and engineers in this technology field are generally unavailable for all countries.

knowledge. I address the second issue by including a variable capturing the heterogeneity across national patent institutions.[34]

Specifically, I construct a country's stock of technical knowledge in quake-proof buildings using patent counts based on the following formula used in R&D literature (e.g., Popp, 2003; Popp et al., 2011).

$$TK_{c,\,t} = \sum_{S=0}^{\infty} e^{-\beta_1(S)} (1- e^{-\beta_2(S+1)})\, PAT_{c,\,t\text{-}s} \tag{6}$$

In this equation, β_1 represents a rate of decay to capture the obsolescence of older patents. β_2 represents the rate of diffusion, which captures delays in the flow of knowledge. The rate of diffusion is multiplied by (s+1) so diffusion is not constrained to be zero in the current period. S is the number of years before the current year t. All patents are sorted based on their first application date. *PAT* stands for the total count of quake-proof building-related patents in country c during the period of t-s. I follow the convention in the literature by assuming a decay rate of 0.10 and a diffusion rate of 0.25.[35] For ease of interpreting the effect of knowledge stock, I use the log of the value of knowledge stock plus 1 in the regressions.

I use the same formula to calculate the foreign knowledge stocks based on foreign patent counts that are computed as total global patents minus the country's own patents in a given year. However, one issue that arises is that the value of patented inventions usually varies widely, partially because the heterogeneity in patent systems across countries make it problematic to value each patent equally. Although this issue is less severe for examining domestic knowledge stocks because I simultaneously control for country-level patent institutions, it may cause serious concerns if I

[34] Because a majority of the countries included in my sample are developing countries that do not even have a patent system in place, their patent counts are coded as zero.
[35] The parameters (the rates of decay and diffusion) used in this paper provide a lag peaking after 4 years, which is consistent with the length of lag structure for R&D capital in the literature. For example, Griliches (1995) notes that most past studies suggest a structuring peaking between 3 and 5 years.

simply sum up all the patents filed worldwide by year. To address this issue, I follow Popp et al. (2011) by weighting patent counts by their patent family size to account for the variation in the values of these patents. I provide a detailed description of the weighting scheme in Appendix 2.

4.2 Country characteristics

I use the data on real GDP per capita from Penn World Table (7.0 version) to measure a country's income. I use the political rights variable from Freedom House as a proxy for the quality of political institutions, which takes a value from 1 to 7, with higher values suggesting fewer political rights in the country. Drawing upon the prior studies modeling disaster damages, I include other country variables, including urbanization status (measured by the percentage of people living in urban areas in a country), openness (constructed as the average ratio of exports and imports of goods and services in GDP), and quality of the public health system (measured by the mortality rate of children under five). To control for countries' patent systems and general propensity to patent innovations, I use the total number of patent applications filed within the country by its residents. All these data are drawn from the World Bank Development Indicators. Finally, I control for a country's size using data on population from Penn World Table and total geographic area from the Global Rural-Urban Mapping Project (GRUMP).[36]

4.3 Earthquake data

The raw data on earthquake losses (deaths and estimated monetary damages) and physics (magnitude and focal depth) are taken from the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Center (NGDC) Significant Earthquake Database. This

[36] Note that in this paper I also include a variable measuring the local population exposed to individual earthquakes, which is discussed in the next subsection.

database includes an earthquake event if it meets at least one of these criteria: at least $1 million damage was incurred; ten or more people were killed; the earthquake had a magnitude 7.5 or greater or Modified Mercalli Intensity X or greater, or the earthquake generated a tsunami.[37]

Using this dataset, I create two additional variables measuring a country's prior earthquake history and population exposed to individual earthquakes, respectively. First, instead of simply calculating the total number of quakes within a certain period as other studies have, I create an experience stock using the number of quakes above magnitude 5 that occurred since 1900 ($Quake_{ct}$) based on the perpetual inventory model (PIM), assuming the experience stock depends on a distributed lag of the current and past events:[38]

$$EXP_{c,t} = Quake_{c,t} + (1-\rho)\, EXP_{c,t-1} \tag{7}$$

ρ is the rate of stock depreciation, which is assumed to be 15 percent following the conventional literature. This approach distinguishes my study from most other research focusing on disaster exposure/propensity as a time-invariant attribute for two main reasons. First, even if the physical propensity of a country to experience certain natural hazards is constant from a statistical point of view, people may not perceive the risk or propensity at the same level over time. Social learning is a gradual process in which people accumulate more and more knowledge over time. It is problematic that earlier studies use a frequency measure that covers the entire estimation period when this value can only be realized at the end of the period (Neumayer et al., 2014). More importantly, the findings in the natural hazard literature suggest that more recent disaster experiences lead to a larger social response in disaster prevention and mitigation, even after

[37] The NGDC earthquake data are compiled from multiple sources, including the U.S. Geological Survey, EM-DAT, reconnaissance reports, regional and local earthquake catalogs, newspapers and journal articles.

[38] I choose to use magnitude 5 as the threshold here because earthquakes that measure 5 on the Richter scale can cause moderate damages. For sensitivity tests I have also used magnitude 6 as another threshold and find both measures are highly correlated. Note that quake is a count variable. If the country does not experience any earthquakes or experiences quakes below 5, it is coded as zero.

controlling for the long-term hazard exposure of the affected areas (e.g., Gallagher, 2014; Cameron and Shah, 2013; Miao and Popp, 2014).[39] Using a discounting model such as PIM implies that earthquakes that occurred earlier become less relevant for today (i.e., memories about the earlier events eventually wear off) and social learning is more responsive to the most recent events. For consistency with my measure of knowledge stock, I also use the logged value of experience stocks plus 1 in the regression.

An earthquake can cause significant damages when it occurs in a heavily populated area. To measure the size of the population exposed to individual quakes, I use the coordinates information for earthquake locations provided by the NGDC database to calculate the number of people living within a 100-kilometer radius around the epicenter using the GPW spatial population data.[40]

One key issue with the NGDC database is that a considerable proportion of the earthquake events recorded in this dataset have missing values for fatalities and monetary damages.[41] It is important to point out that this issue is not specific to the NGDC dataset, but essentially common in other more widely-used disaster databases such as the EM-DAT maintained by the Centre of Research on the Epidemiology Disaster (CRED).[42] If the data on the dependent variable are

[39] For example, Gallagher (2014) finds that the U.S. county-level flood insurance take-up rates increase sharply the year after a flood occurred and then gradually declines to the normal level. Note that while these studies focus on the mechanism that recent events update people's risk perception, this research focuses on learning by asking whether recent experience can mitigate future disaster impacts.

[40] This procedure is done using the Arcmap by intersecting the population distribution map taken from the Gridded Population of the World (GPW), v3 (http://sedac.ciesin.columbia.edu/data/collection/gpw-v3/about-us) with the earthquake event map. I used the population data of 1995 and interpolate the annual data on the local population exposure variable by taking into account a country's overall population growth.

[41] Specifically, about 55 percent of the earthquake events for my sample countries in the NGDC database do not have information on deaths, and 80 percent of them have no information on monetary damages. According to the NGDC data manager, the earthquake loss data are missing because of two reasons: 1) coding error. When earthquake caused no deaths, it is coded as missing rather than zero. Therefore, the NGDC raw data do not have any events coded with zero deaths or damages; 2) truly missing. There is no information available about the exact losses.

[42] The EM-DAT states that "0" does not represent a value and can mean no information available. But in almost all studies that use EM-DAT data, 0 is explicitly treated as zero deaths/damages instead of missing. One reason that researchers are not aware of this problem is because the disaster data (available for direct downloading in advanced search) have been already collapsed to country-year observations as a balanced panel. The disasters impacts are all coded as "0" if a country has not experienced a disaster or has missing deaths/damages when a disaster strikes.

missing completely at random (i.e., the probability of having missing values is neither dependent on other observed variables nor the value of the variable itself), the analysis should still provide unbiased estimates (Graham, 2009). However, here the missing data are not random because: first, the missing values include earthquakes that resulted in zero deaths or damages (but we don't know exactly which portion of the missing data are true zeros or truly missing); and moreover, my investigation of the potential causes of missing data shows that smaller-magnitude earthquakes that occurred more deeply in the crust, and also in less populated areas, are more likely to have missing values on deaths and damages.[43] This may suggest that one possible missing mechanism might be these earthquakes caused very few losses which are therefore unreported (in other words, the missingness may depend on the value of the outcome variable itself). In the next sub-section I discuss in more detail how I address the missing data issue by employing different estimation strategies.

4.4 Empirical model and estimation strategies

Based on my conceptual model, I estimate the following equation to examine the effect of technical knowledge and experience stocks on earthquake fatalities:

$$\mathrm{Log}(deaths_{e,c,t} + 1) = \mathrm{f}\,(M_{e,c,t},\ POP_{e,c,t},\ \boldsymbol{TK_{c,t-1}},\ \boldsymbol{EXP_{c,t-1}},\ Y_{c,t-1},\ I_{c,t-1},\ X_{c,t-1},\ c_{ontinent},\ \theta_t,\ \varepsilon_{e,c,t}) \qquad (8)$$

where *e* is an earthquake event indicator, *c* a country indicator, and *t* a year subscript. This model accounts for both event characteristics (magnitude, focal depth, population exposure), and country

[43] Specifically, I create a binary variable which indicates whether an event has missing deaths or damage, and regress it on both earthquake characteristics and country characteristics variables using a probit model. I provide the regression results and more details on missing data in Appendix 3.

characteristics (knowledge and experience stocks, income, political rights, urbanization, trade openness, child mortality rate, patent applications, population and geographic size). To avoid potential endogeneity, I lag all the country-level variables one year. In the model, I also include continent fixed effects to control for the geopolitical heterogeneity and year fixed effects to account for time-varying factors that are common to all countries (e.g., improvement in other types of earthquake-preventive technologies over time).[44] It should be noted that the unit of observation in my analysis is an earthquake event.[45] Therefore, I only include an observation when a country experienced an earthquake in a given year. Repeated country-year observations are thus included in the regression when the country experienced multiple events within the same year.

As noted earlier, one empirical challenge in modeling earthquake damages is to deal with a large number of missing values on the outcome variable. In previous studies, most researchers treated missing deaths as zero, especially when they collapsed events to the country-year observations. Because the NGDC's missing data do include zero deaths and are also associated with smaller and less destructive earthquakes, it seems relatively safe to assume these missing values may indicate very few deaths. Therefore, I start with the strongest assumption (i.e., missing is zero) and estimate equation (7) using an ordinary least squares (OLS) and Tobit model.[46] I then relax this assumption by left censoring all the missing deaths at ten, given that ten deaths are one of the thresholds for including an earthquake in the NGDC database.[47] Under this assumption, I estimate the same equation using a censored normal regression, which is one variation of the Tobit

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[44] Note that including controls for time is particularly important in this case. Because the knowledge stocks generally increase over time, year dummies help rule out the possibility that the knowledge stocks only pick up other tendencies for earthquake damages to decrease over time.

[45] I construct my data set based on earthquake events on purpose so I can still keep the events with missing deaths or damages in my sample.

[46] Because the earthquake deaths and damages can never be negative, this "corner solution situation" generally renders OLS inappropriate as an estimation methodology and make a Tobit estimator more preferable (Woodridge, 2006).

[47] Note that this approach assumes all the events with missing deaths have killed no more than ten people. It is more conservative to use a wider range (<10 deaths) than assigning a specific value (zero).

model.[48]

Finally, I use the Heckman selection model (Heckman, 1979) to first predict the events that have non-missing deaths and then model the earthquake fatalities in the second stage.[49] One advantage of using a selection model is that I don't impose any explicit restrictions on the missing values, since it takes into account the missing data mechanism. To model the first-stage selection process, I use a tsunami indicator (a binary variable coded as 1 if the earthquake has generated a tsunami and 0 otherwise) as an instrumental variable. Recall that the occurrence of tsunami is one of the criteria for including an earthquake into the NGDC database. In particular, there is a considerable number of earthquakes in this database that were tsunamigenic but with no information on their actual impacts. Therefore, the tsunami indicator can qualify as an instrument because first, as a criterion imposed by data collectors, it affects the selection process by bringing in many non-destructive events with missing deaths, and at the same time, it does not directly correlate with my dependent variable, which is measured by direct deaths from earthquakes only (not including any secondary effects caused by earthquakes).

In addition to fatalities, I also use monetary damages as another measure of earthquake impact, which is normalized as a fraction of the affected country's GDP, $\log[\text{damage}_{ct} / \text{GDP}_{ct-1} + 1]$.[50] Note that censoring models are no longer appropriate for modeling damages because there is a non-negligible number of earthquakes that have missing values for dollar damages but are estimated to

[48] I estimated this model using the "cnreg" command in Stata.
[49] Specifically, the first stage is run on the full sample of earthquake events using a probit model, and models the events which have non-missing deaths, considering this group is systematically different from the group with missing deaths. The second stage, the conditional equation, is an OLS model run only on the events with non-missing deaths and also includes a variable, the inverse Mills ratio which is obtained in the first stage and controls for selection into this subsample. The Heckman selection model imposes exclusion restrictions, which means I need to identify an instrument variable that determines the probability of having missing values but not directly affect the earthquake losses.
[50] Because the damage-GDP ratio is a very small number for most countries in my sample, I multiply the fraction by one million before taking the log.

have caused severe property losses.[51] Therefore, I only employ the Heckman selection model with the tsuami indicator as the instrumental variable in the case of damages. For all these models discussed above, I use robust standard errors clustered at the country level to account for potential heteoskedasticity.

4.5 Sample and descriptive statistics

Considering the fact that small earthquakes may cause only minor damages or not even be felt, I limit my sample to earthquakes of magnitude 5 and above.[52] My final sample includes a total of 894 earthquakes that occurred in 79 countries over the period 1980-2010.[53] I chose 1980 as the starting year in this study because the patent data generally become available in the mid 1970s, and I allow the knowledge stock to accumulate over several years before entering the regressions.

Table 2-1 provides the national summary statistics reporting the sampled country's total earthquake counts, total earthquake-related deaths and damages, and total counts of patents in quake-proof building technologies over my study period. All the monetary damages are adjusted at the 2005 level by the World Bank GDP deflator index. Notably, 17 countries out of the sample have patents in the given technology field, and among all the patenting countries, Japan, United

[51] This is inferred based on a five-level categorical variable provided by the NGDC to classify earthquake-related monetary losses. Specifically, this variable classifies damages as follows: 0 = none; 1 = limited (roughly corresponding to less than \$1 million); 2 = moderate (~1 to 5 million); 3= severe (~>5 to 24 million) and 4 = extreme (~\$25 million or more). This variable is available for most of the events in the dataset, which thus allows me to gauge the losses of earthquakes with missing damages. I find that half of the events with missing damages have caused less than \$1 million damages, while about 20 percent of these events are estimated to have caused at least \$5 million damages.

[52] I performed a test by including almost all the earthquakes in the NGDC database regardless of their magnitude, and examining whether a country's knowledge stocks and experience stocks have differential effects across different scales of earthquakes. In the results provided in Appendix 4, I show that although the two variables have a significant and negative effect on fatalities for earthquakes measuring 5 and above on the Richter scale, they are generally insignificant for quakes below this threshold. This suggests that the role of knowledge in disaster mitigation is more pronounced for larger earthquakes.

[53] This sample includes all such earthquakes for which complete data is available for all independent variables.

States, China and Republic of Korea have filed most patent applications.[54] Figure 1 shows the global patent counts in quake-proof buildings over time. Table 2-2 reports the descriptive statistics of the main variables in the analysis.

5. Results

5.1 The effect of domestic knowledge

Table 2-3 presents the regression results for equation (8) using earthquake fatalities as the dependent variable in four different estimation models as discussed earlier. Across different columns, I find consistent evidence that both the technical knowledge and experience stocks have statistically significant and negative impacts on earthquake fatalities. The marginal effects for the technical knowledge and experience stocks indicate that, all else constant, a 10% increase in the knowledge stock is on average associated with 2% to 3.5% decrease in expected earthquake fatalities, and a 10% increase in the experience stock is associated with a 4.3% to 5.8% decrease in expected fatalities.[55] Notably, using the Heckman selection model and Tobit model (assuming missing is zero) yields higher estimated coefficients for knowledge and experience stocks compared to the other models.

One thing is important to note here. Unlike some other studies that use the cumulative counts or average disaster frequency to characterize a country's disaster risk that is constant over time,

[54] It should be noted that there are other countries that have patents in quake-proof building technologies but are not included in the sample because they did not experience any large earthquakes during the sample period, such as Germany. But their patents are counted in the global pool and are used to calculate the foreign patents and knowledge stocks. Also note that Japan has significantly more patents than other countries because its patent systems require the inventors to file multiple patents for the same invention which would otherwise be covered by a single patent in other countries. This is why it is important to control for a country's patent regime in this study.

[55] Note that the OLS (column 1) and Tobit model (column 2) are performed under the same assumption that missing deaths are zero, and in this case the latter is generally considered to provide more reliable estimates because of the non-negative nature of deaths. Therefore, I primarily focus on columns 2-4 in my discussion of the results. Also note that Tobit, censored normal, and the Heckman selection models are all modeling linear effects on the latent variables, not the observed outcomes. Their coefficients are interpreted in the similar manner to OLS regression coefficients.

the experience stock I construct here is a time-varying variable for individual countries, which assigns more weight to more recent earthquake events the country has experienced. Even though these two measures are highly correlated, they entail different conceptual implications. In the results I provide in Appendix 5, I test their respective explanatory power by including both such variables in the regressions and find that the experience stock still remains statistically significant and negative while the constant frequency measure becomes insignificant in all cases. This may suggest the dynamics of learning in disaster mitigation and, in particular, that the events that occurred more recently play a more important role in updating people's knowledge on coping with earthquakes. In addition, I also show my estimation results are robust to using the experience stock variable constructed with earthquakes above magnitude 6.

All the event-specific variables (including earthquake magnitude, focal depth and size of exposed population) are significant for explaining fatalities, and have the expected sign. In terms of other country characteristics, it is interesting to see that a country's income is insignificant, despite the strong consensus reached in the prior literature on the mitigating effect of economic development. Notably, I include logged GDP per capita and its squared term to allow for the nonlinear income-mortality relationship (Kellenberg and Mobarak, 2008), and an F-test shows the two variables are not jointly significant. In the results provided in Appendix 6, I show that when I exclude knowledge stocks (which highly correlate with a country's income level), the GDP variables become statistically significant and exhibit the same pattern as found in Kellenberg and Mobarak (2008). This finding may suggest that an important channel that income mitigates disaster impacts is through development of technical knowledge, since the inclusion of knowledge stock lowers the explanatory power of income for earthquake fatalities.

Consistent with the findings from prior literature, my results show that the quality of political institutions is another important determinant of earthquake fatalities, because the estimated coefficients suggest that countries with greater political rights suffer significantly fewer deaths from earthquakes. Another variable that is consistently significant across all models is the child mortality rate, with a positive estimated coefficient. This suggests that earthquakes of the same intensity would result in more fatalities in countries with poorer public health systems. None of the past studies have specifically examined this factor and I argue that the effect of health conditions on disaster risk deserves more attention in future empirical research in this field.

To investigate whether the effect of the experience stock on earthquake fatalities differs across countries at different income levels, I estimate separate experience coefficients for developed and developing countries. Specifically, I create two binary variables: one variable equaling one if a country is a developed country and zero otherwise, and the other variable equaling one if a country is a developing country and zero otherwise. I interact both variables with the experience stock in order to directly compare the estimated effect of prior earthquake experiences in developed nations *versus* the effect on developing nations. Table 2-4, Panel A reports the results for the interaction terms and knowledge stocks.[56] I find that while developing countries with more prior earthquake experiences on average have significantly fewer fatalities from earthquakes, the estimated effect of experience is less clear in the developed world. The coefficients are insignificant in columns 2 and 4, and significant at only the 10% level in column 3. This is not surprising because developed countries usually have more patented innovations and their innovations in earthquake mitigation could also be motivated by their past earthquake experiences, as suggested in Miao and Popp (2014). The high correlation between this interaction term and the domestic knowledge stock may

[56] The estimated coefficients for other independent variables remain largely the same as in Table 2-3 and therefore, are not included in this table.

thus introduce multicollineary. Note that the estimated coefficients for the technical knowledge variable are still significant and negative, although their significance declines slightly compared to the results in Table 2-2.

Considering the potential multicollineary issue, I re-run the same specifications after removing the knowledge stock so I can compare the full effects of experience stocks between the two groups. According to the results reported in Table 2-4, Panel B, the estimated coefficient for the experience stock in developed nations is now statistically significant and their magnitude is consistently larger than that of the experience coefficient in developing countries. Furthermore, I find that the two coefficients are significantly different from each other at the 10% level in most of my specifications. This suggests that developed countries are generally more responsive to their past disaster experiences, and that they have stronger adaptive capacity to translate their experiences into effective protection against current disaster shocks. Combining the results in Panel A, I can also infer that technological innovation is one important channel for developed nations to engage in social learning and develop new knowledge to mitigate future disaster risks.

In addition to fatalities, I also use monetary damages as another measure of earthquake impact. Table 2-5 reports my estimation results using a Heckman selection model, which aims to address the issue of missing data on dollar damages.[57] Column 1 presents the baseline result, which shows the experience stock still has a significant and negative effect on earthquake damages, while the domestic knowledge stock becomes insignificant, suggesting that the accumulation of quake-mitigating innovations in a country can save more lives when an earthquake occurs but may not be that effective in reducing property losses. In column 2, I interact the expereince stock with developed and developing dummies to see whether the past disaster experiences may exert

[57] The independent variables included in the damage model are largely the same as those used for modeling fatalities. The only difference is I removed the child mortality rate, because this variable is less relevant for damage outcomes.

differential impacts on earthquake damages across different country groups. In contrast to the results in Table 2-4, I find that prior experience has a significant mitigating effect in developed countries (a 1% increase in their experience stock is on average associated with a 3% decrease in normalized earthquake damages), while the estimated coefficient of experience for developing nations becomes statistically insignificant. The domestic knowledge stock is also insignificant in this case.

With respect to other control variables, I find the event-specific factors are consistently significant for explaining the severity of earthquake damages. The results on other country-level variables are less clear, potentially because I include the developed and developing dummies in the second regression. For example, the political right variable is found to be statistically significant and positive in column 1, although this variable is no longer significant in column 2.

One important thing to note here is that reporting on deaths has been traditionally more accurate than damage reports, because the latter could be highly subject to the country heterogeneity in disaster loss measurement and reporting (Kousky, 2013). Monetary damages from natural disasters usually involve direct losses (e.g., destruction of capital stocks) and indirect losses (e.g., welfare effects), which adds more complications to the evaluation of actual damages. Since the NGDC database contains more missing values for earthquake damages than deaths, this makes it even more difficult to model the factors which explain the cross-country pattern of earthquake damages. Considering this specific data limitation, I have more confidence in the results when using fatalities as the measure of earthquake impact.

5.2 The effect of foreign knowledge

Since my results from Tables 2-3 and 2-4 suggest that a country that has accumulated more technical knowledge in earthquake-mitigation would suffer fewer fatalities, I take a further step by asking whether one country's technical innovations might benefit other countries in reducing their own disaster risks, given the public good nature of innovation. To investigate the potential knowledge spillover effect, I estimate equation (8) by including the foreign knowledge stock variable that is constructed based on foreign patents in quake-proof building technologies. It should be noted that the foreign knowledge stock is, by construction, more or less the same for all countries, because foreign knowledge for non-patenting countries is equivalent to the global knowledge stock. It is also similar for all the patenting countries because each of them only contributes a relatively small number of patents to the global pool. When countries exhibit very similar time-varying trends in the foreign knowledge stocks, it is difficult to identify the effect of foreign knowledge independent of the individual year dummies. Therefore, instead of the year fixed effects, I include linear time trend and its quadratic term in the regressions.

Two issues are important to note here. First, although the stock of foreign knowledge available for individual countries is similar, one may doubt whether foreign knowledge is equally accessible to and exploited by every country. In other words, the effect of the foreign knowledge stocks in disaster mitigation is very likely to vary across the recipient countries depending on their characteristics. Here I consider two specific mediating factors. First, drawing upon the literature on international technology diffusion suggests that knowledge spillovers are often likely to occur throughout international trade (Coe and Helpman, 1995), I hypothesize that countries that are more open to trade would have better access to foreign knowledge and thus, are more likely to apply it in their own disaster mitigation endeavors. Furthermore, countries that are more prone to earthquakes might be more interested in introducing new quake-mitigating technologies that have been developed abroad, and also their past experiences may also provide them stronger absorptive capacity to exploit foreign knowledge for disaster mitigation. To examine these two hypotheses, I interact the foreign knowledge stock with a country's trade openness and experience stock, respectively, to test whether the increase in foreign knowledge exerts differential effects across countries conditional on these characteristics.

Second, it always takes time for technical innovations to diffuse from one country to the other. Since I use one-year lagged values of the domestic knowledge stocks, it is reasonable to assume that the effect of foreign knowledge would take longer than one year to realize. I conduct a set of sensitivity tests with different number of lags (more details on the sensitivity analysis provided in Appendix 7) and here I present the results using foreign knowledge stock lagged by five years.

Table 2-6, Panel A reports the results when the foreign knowledge variable is included. Panel B includes the interaction term between foreign knowledge and trade openness, and Panel C includes the interaction between foreign knowledge and experience stocks. My results generally do not provide strong evidence on the mitigating effect of foreign knowledge in quake-proof building, as the coefficient on foreign knowledge is negative but not statistically significant. There is also little evidence that the effect of foreign knowledge varies with the receiving country's trade openness and past earthquake experiences, because neither of the interaction terms is statistically significant. In the meantime, including the foreign knowledge stocks does not change the significance and magnitude of the estimated coefficients of domestic knowledge stocks. This finding may suggest that compared to domestic knowledge stocks, foreign knowledge is less effective in reducing a country's disaster risk. This might be because the quake-proof building technologies are specific to local geography (Lanjouw and Mody, 1996) or that building and infrastructure construction is largely a local industry, which make it more difficult for these specific innovations to diffuse across countries.

Another reason that may cause the insignificance of foreign knowledge is multicollinearity, because the stock variable gradually increases over time and highly correlates with the time trend variables. Thus, I take a further step by asking whether there has been a global downward trend in earthquake fatalities, given that technologies are always improving over time (including not only quake-proof buildings, but also other relevant techniques such as detection, warning, debris removal) that may contribute to the global adaptive capacity in general. In the results provided in Appendix 8, I re-run the regressions by removing the foreign knowledge stock but still keeping the time trend variables to account for the general global technological progress in earthquake mitigation. I find that the time variables are still statistically insignificant, which indicates that in the past thirty years there has been no significant decrease in earthquake fatalities worldwide after controlling for country-specific attributes. This may suggest that disaster mitigation relies more on the efforts of affected countries themselves rather than the advancement of global knowledge.

6. Discussion and conclusion

Considerable work has been devoted in the past decade to modeling damages of natural disasters to understand the factors that determine a community or nation's ability to cope with them. This growing literature not only informs policies for natural hazard mitigation, but also has important implications for climate change adaptation, particularly given the growing scientific consensus that climate change could worsen certain natural disasters.[58] This paper extends this line of

[58] Although the focus of this paper is on earthquakes which obviously have a weaker link to climate change, we could potentially consider the responses to earthquakes as an analogue of the responses to climate change and climate-related extreme events.

literature by considering knowledge as an important determinant and indicator of social capacity to adapt to natural disasters. Specifically, I present the first attempt to empirically examine the role of technical innovation in disaster risk mitigation by making use of patent data to track the technological change. Because innovation is only one form of social learning, I also account for a country's prior earthquake experience considering it as not only the motivation for learning, but also a measure of the unobserved informal knowledge for coping with earthquakes. My results provide strong evidence that countries that have more innovations in quake-proof building technologies and were more exposed to earthquakes in the past suffer significantly fewer fatalities from later earthquakes. Moreover, I show that past quake experiences result in a larger mitigating effect in developed countries than in developing countries, though this difference could be partially explained by the stronger capacity of industrialized nations to develop new and more effective risk-mitigating technologies.

An important distinction between this study and prior research that examines country-level baseline hazard is that I place my conceptual argument for disaster mitigation in a learning framework, and emphasize that past events that occurred at different points in time may have differential implications for learning, since the effects of earlier events may eventually wear off. This approach not only provides a better understanding of adaptation as a dynamic learning process, but also sheds light on what drives society to adapt to environmental changes and shocks. This research further informs the modeling of potential future climate damages and climate adaptation (e.g., de Bruin et al., 2009; Bosello et al., 2009), as my results may suggest that past experiences with climate variability and extreme weather events would motivate adaptation, which in turn, reduces the future damages of climate change.

This paper also makes an important methodological contribution to the empirical literature on natural disasters by addressing the issue of missing data on disaster fatalities and damages. Moreover, I use multiple estimation strategies to model earthquake fatalities, which produce consistent results across different specifications. Because the EM-DAT data that are most commonly used in current disaster research also have this data limitation, it is important for researchers to carefully think about how their choice of models and data structure (based on country-year or events) may relate to assumptions regarding the missing deaths and damages, and ultimately affect their estimation results. I envision my study provides a starting point for more discussion and investigation of this empirical challenge.

Finally, given my findings on the effect of technical innovation on reducing earthquake fatalities, this research highlights the importance of incorporating technology development into an integrated policy approach for natural hazard mitigation and climate adaptation. While the traditional literature suggests economic development and institution improvement can provide "implicit insurance" against natural disasters (Kahn, 2005), this research suggests that countries adjust their allocation of resources in mitigation-specific investment and put more effort into encouraging the development of risk-mitigating technologies. Concerning the global diffusion of these technologies, in this paper I did not find strong evidence on the effect of foreign knowledge on reducing domestic earthquake fatalities. However, this does not suggest that foreign knowledge does not matter. One possibility could be that countries tend to rely more on their domestic knowledge in risk mitigation and do not effectively exploit the technical innovations available abroad. If this is the case, one policy recommendation is that international institutions should play a more important role in encouraging and facilitating technology transfer of risk-mitigating technologies between the developed and developing world. I leave studying the implications of foreign knowledge and knowledge spillovers for future research.

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Table 2-1 Earthquake and patent statistics for sample nations

country	# of 5+ earthquakes	Total deaths (persons)	Total damages (million $, adjusted at 2005 price)	# of Patents
Afghanistan	26	9204	66.72598	0
Albania	3	0	0	0
Algeria	10	7509	16269.53	0
Argentina	5	9	8.11293	10
Armenia	1	0	0	0
Australia	4	12	1.580914	12
Austria	1	1	0	7
Azerbaijan	2	32	5.757715	0
Bangladesh	4	5	0	0
Belgium	1	2	86.73025	8
Bhutan	5	11	0	0
Bolivia	1	105	0	0
Bulgaria	1	3	7.93777	8
Canada	2	0	0	35
Chile	27	605	29525.37	0
China	94	92072	114574.6	291
Colombia	11	1551	2203.106	0
Congo, Dem. Rep.	4	54	0	0
Costa Rica	9	130	719.0294	0
Croatia	1	0	0	0
Cuba	1	0	0	0
Cyprus	1	2	5.317976	0
Dominican Republic	2	8	0	0
Ecuador	10	1050	1098.794	0
Egypt	3	557	1566.58	0
El Salvador	5	2303	2858.237	0
Ethiopia	2	0	0	0
Fiji	5	5	0	0
France	1	0	0	134
Georgia	1	0	0	0
Greece	29	218	3686.261	31
Guatemala	9	33	0	0
Haiti	2	222574	7207.856	0
Honduras	4	12	0	0
Iceland	3	0	36.06854	0
India	27	33217	3603.956	0
Indonesia	107	11742	15840.01	0
Iran	74	81214	13859.2	0

Continued on the next page

Italy	15	5060	49344.18	42
Japan	65	5769	166315.4	9928
Jordan	1	0	0	0
Kazakhstan	1	1	0	0
Kyrgyzstan	8	131	210.1828	0
Laos	1	0	0	0
Lebanon	1	0	0	0
Macedonia	3	1	9.015505	0
Malawi	3	13	40.24146	0
Mexico	27	9962	6951.751	10
Morocco	1	628	0	0
Mozambique	1	4	0	0
Nepal	3	1291	708.7818	0
Netherlands	1	1	130.5483	11
New Zealand	17	3	323.9742	29
Nicaragua	4	7	0	0
Pakistan	16	86556	5219.308	0
Panama	8	2	0	0
Papua New Guinea	20	87	57.84026	0
Peru	26	853	20.83241	0
Philippines	28	2685	526.5851	0
Portugal	4	79	94.59422	0
Republic of Korea	1	0	0	217
Romania	7	18	1191.713	23
Russia	14	2018	15069.15	79
Saudi Arabia	1	0	0	0
Slovenia	1	1	0	0
Solomon Islands	15	55	0	0
South Africa	1	15	0	0
Sudan	3	33	0	0
Tajikistan	5	68	1.351473	0
Tanzania	2	2	0	0
Thailand	1	0	0	0
Tonga	1	0	0	0
Trinidad and Tobago	3	1	29.54035	0
Turkey	39	20442	24503.51	0
Turkmenistan	1	11	0	0
Uganda	1	7	87.56567	0
United States	59	149	54131.79	323
Vanuatu	14	5	0	0
Venezuela	10	98	106.864	0

Notes: While the earthquake counts and impact data cover the period 1980-2010, my patent data reflect the total counts of patent applications filed between 1974 and 2009.

Table 2-2 Descriptive Statistics

	Mean	Std. Dev.	Min	Max	N
Independent variables					
EXP*	1.96	0.95	0	3.66	897
TK*	1.22	2.08	0	7.96	897
FTK#	5.81	1.01	2.83	6.76	897
Magnitude	6.24	0.81	5	9.1	897
Focal Depth (kms)	31.69	53.97	0	675	897
log(exposed population)	19.62	3.42	0	24.25	897
log(GDP per capital)*	8.66	1.07	5.23	10.69	897
Political Rights*	3.41	2.15	1	7	897
log(population)*	17.86	2.03	11.55	21	897
Urban* (%)	53.78	21.7	5.84	95.6	897
Health* (%)	4.37	3.54	0.29	23.44	897
Open*(%)	26.08	12.98	6.17	82.69	897
log(patent applications)*	6.12	3.75	0	12.86	897
log(area)	13.7	1.74	6.5	16.63	897
Dependent variables					
log(death+1)[a]	2.48	1.53	0.69	12.31	897
log(death+1)[b]	2.68	2.19	0.69	12.31	429
log(damage+1)[b]	4.69	2.95	0.15	13.22	206

Notes: Varibales with * are one year lagged, and # indicates five-year lagged value. Log(death+1)[a] indicates that all the missing deaths are replaced as zero, while variables with "b" are logged with only the non-missing values.

Figure 2-1. Global patent counts in quake-proof building, 1974-2009

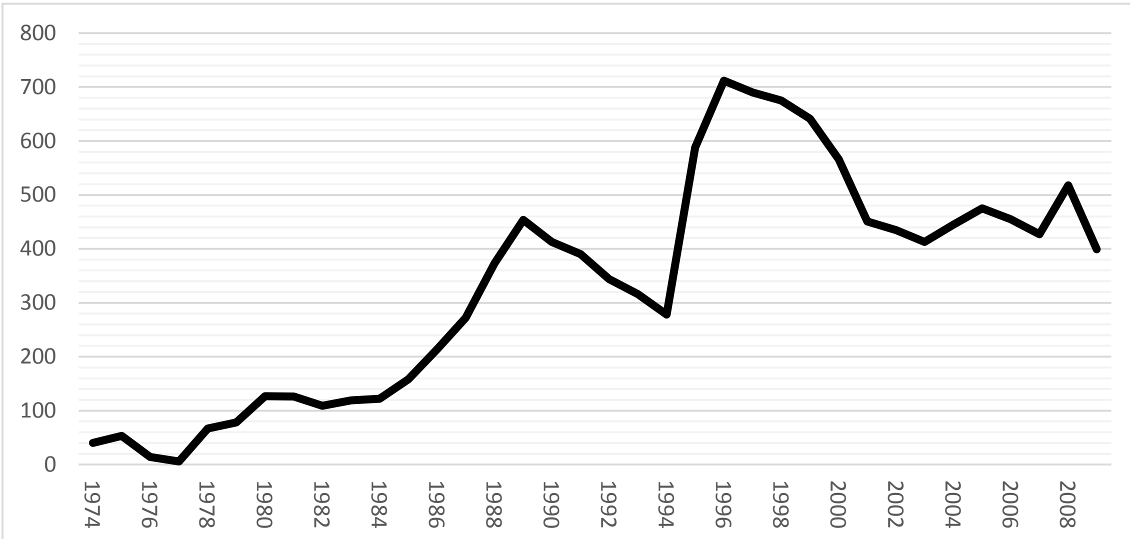

Table 2-3 Modeling the effect of knowledge on earthquake fatalities [DV: log(death +1)]

Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection
EXP (t-1)	-0.364***	-0.470***	-0.436***	-0.582**
	(0.104)	(0.178)	(0.127)	(0.238)
TK (t-1)	-0.174***	-0.348***	-0.201**	-0.318*
	(0.0649)	(0.115)	(0.0860)	(0.163)
magnitude	1.278***	2.356***	1.795***	2.697***
	(0.175)	(0.227)	(0.211)	(0.421)
focal depth	-0.00341***	-0.0125***	-0.00930***	-0.0130***
	(0.00108)	(0.00365)	(0.00242)	(0.00392)
log(exposed population)	0.155***	0.502***	0.353***	0.534***
	(0.0300)	(0.117)	(0.0810)	(0.116)
log(GDP per capital) (t-1)	1.185	0.993	1.745	2.517
	(1.148)	(2.022)	(1.408)	(2.375)
[log(GDP per capital)]^2(t-1)	-0.0501	-0.0327	-0.0854	-0.132
	(0.0701)	(0.128)	(0.0896)	(0.145)
political rights(t-1)	0.132**	0.214**	0.144*	0.239**
	(0.0557)	(0.100)	(0.0744)	(0.0988)
log(population)(t-1)	0.206	0.233	0.127	0.154
	(0.153)	(0.298)	(0.209)	(0.264)
urban (t-1)	0.00314	0.00730	0.00260	0.00753
	(0.00787)	(0.0140)	(0.0103)	(0.0159)
health (t-1)	0.0923**	0.179***	0.104**	0.168**
	(0.0441)	(0.0685)	(0.0478)	(0.0826)
open (t-1)	-0.0148**	-0.0110	-0.0156	-0.0242
	(0.00681)	(0.0156)	(0.00994)	(0.0159)
log(patent applications) (t-1)	0.0101	0.0630	0.0271	0.0731
	(0.0475)	(0.0912)	(0.0567)	(0.101)
log(area)	-0.0732	0.0170	0.0456	-0.0121
	(0.155)	(0.260)	(0.201)	(0.222)
Constant	-17.99***	-34.81***	-27.66***	-41.38***
	(5.133)	(8.996)	(6.178)	(11.85)
Left censored		465	465	
N	894	894	894	894

Notes: All the models include continent fixed effects, year fixed effects, with robust standard errors clustered at the country level.

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

Table 2-4 Interacting expereince with developed and developing country dummies

Panel A - DV: log(death +1)				
	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
Developed * EXP(t-1)	-0.433**	-0.612	-0.545*	-0.716
	(0.174)	(0.417)	(0.288)	(0.447)
Developing* EXP(t-1)	-0.344***	-0.438**	-0.412***	-0.549**
	(0.111)	(0.180)	(0.128)	(0.245)
TK(t-1)	-0.161**	-0.320**	-0.179*	-0.287*
	(0.0696)	(0.132)	(0.103)	(0.174)
N	894	894	894	894

Panel B - DV: log(death +1)				
	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
Developed * EXP(t-1)	-0.613**	-0.995***	-0.762***	-1.019***
	(0.174)	(0.324)	(0.227)	(0.386)
Developing* EXP(t-1)	-0.311***	-0.365**	-0.372***	-0.483**
	(0.121)	(0.195)	(0.142)	(0.220)
Test the equality of the two coefficients(prob>F)	0.0927	0.0800	0.0990	0.1650
N	894	894	894	894

Notes: All the models include continent fixed effects, year fixed effects, with robust standard errors clustered at the country level. All the specifications include all the other controls variables.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-5 Modeling the effect of knowledge on earthquake damages

DV: $\log[damage_{ct} / GDP_{ct-1} + 1]$

Independent variables	**(1)**	**(2)**
EXP (t-1)	-0.949**	
	(0.470)	
TK (t-1)	-0.0453	0.306
	(0.235)	(0.310)
Developed * EXP(t-1)		-3.064***
		(1.143)
Developing* EXP(t-1)		0.0323
		(0.579)
magnitude	3.266***	3.594***
	(0.873)	(1.025)
focal depth	-0.0204**	-0.0209**
	(0.00852)	(0.00982)
log(exposed population)	0.769***	0.852***
	(0.217)	(0.255)
log(GDP per capital) (t-1)	-4.550	-9.672*
	(4.521)	(5.819)
$[\log(\text{GDP per capital})]^2$(t-1)	0.304	0.628*
	(0.272)	(0.356)
political rights(t-1)	0.417**	0.278
	(0.166)	(0.196)
log(population)(t-1)	-0.565	-0.341
	(0.417)	(0.492)
urban (t-1)	-0.0419*	-0.0362
	(0.0252)	(0.0290)
open (t-1)	-0.0427	-0.0991**
	(0.0303)	(0.0414)
log(patent applications) (t-1)	0.196	0.285
	(0.172)	(0.204)
log(area)	-0.0625	-0.930*
	(0.383)	(0.505)
Constant	-3.454	22.40
	(22.22)	(24.46)
N	894	894

Notes: All the models include continent fixed effects, year fixed effects, with robust standard errors clustered at the country level. All the specifications include all the other controls variables.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-6 Modeling the effect of foreign knowledge on earthquake fatalities

Panel A - Only adding foreign knowledge stock				
	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
EXP (t-1)	-0.337***	-0.412**	-0.376***	-0.500*
	(0.107)	(0.189)	(0.136)	(0.279)
TK (t-1)	-0.212***	-0.396***	-0.248***	-0.433**
	(0.0689)	(0.115)	(0.0915)	(0.205)
FTK(t-5)	-0.396	-0.567	-0.580	-0.714
	(0.466)	(0.851)	(0.628)	(1.418)
magnitude	1.262***	2.322***	1.761***	2.857***
	(0.177)	(0.243)	(0.221)	(0.524)
focal depth	-0.00326***	-0.0119***	-0.00904***	-0.0144***
	(0.00109)	(0.00397)	(0.00260)	(0.00469)
log(exposed population)	0.155***	0.483***	0.336***	0.590***
	(0.0304)	(0.122)	(0.0832)	(0.148)
log(GDP per capital) (t-1)	1.319	1.279	1.856	2.475
	(1.192)	(2.090)	(1.485)	(2.802)
[log(GDP per capital)]^2(t-1)	-0.0563	-0.0462	-0.0907	-0.124
	(0.0722)	(0.132)	(0.0930)	(0.172)
political rights(t-1)	0.152***	0.250**	0.162**	0.290**
	(0.0560)	(0.0980)	(0.0720)	(0.125)
log(population)(t-1)	0.225	0.288	0.149	0.249
	(0.156)	(0.312)	(0.218)	(0.321)
urban (t-1)	0.00421	0.00944	0.00340	0.0102
	(0.00779)	(0.0139)	(0.0104)	(0.0192)
health (t-1)	0.109**	0.203***	0.121**	0.223**
	(0.0441)	(0.0704)	(0.0509)	(0.104)
open (t-1)	-0.0139**	-0.00966	-0.0157*	-0.0220
	(0.00639)	(0.0144)	(0.00932)	(0.0189)
log(patent applications) (t-1)	0.0251	0.0845	0.0471	0.109
	(0.0493)	(0.0970)	(0.0596)	(0.120)
log(area)	-0.0915	-0.0317	0.0173	-0.0554
	(0.157)	(0.277)	(0.212)	(0.266)
time trend	0.102	0.153	0.136	0.167
	(0.139)	(0.246)	(0.186)	(0.417)
time trend^2	-0.00160	-0.00316	-0.00206	-0.00294
	(0.00252)	(0.00439)	(0.00335)	(0.00727)
Constant	-18.34***	-35.37***	-26.76***	-44.46***
	(5.165)	(9.285)	(6.642)	(14.87)
N	894	894	894	894

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Panel B – foreign knowledge interacted with openness				
	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
EXP (t-1)	-0.326***	-0.380**	-0.359***	-0.456*
	(0.105)	(0.188)	(0.134)	(0.269)
TK (t-1)	-0.208***	-0.388***	-0.244***	-0.412**
	(0.0696)	(0.115)	(0.0921)	(0.195)
FTK(t-5)*open(t-1)	0.00345	0.00985	0.00536	0.0117
	(0.00302)	(0.00652)	(0.00422)	(0.0121)
FTK(t-5)	-0.292	-0.292	-0.433	-0.391
	(0.489)	(0.901)	(0.664)	(1.390)
open(t-1)	-0.0338*	-0.0664	-0.0465*	-0.0898
	(0.0190)	(0.0420)	(0.0261)	(0.0713)
N	894	894	894	894

Panel C – foreign knowledge interacted with experiences				
	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
EXP (t-1)	-0.506	-0.745	-0.454	-0.563
	(0.488)	(0.904)	(0.548)	(0.863)
TK (t-1)	-0.211***	-0.395***	-0.248***	-0.427**
	(0.0690)	(0.114)	(0.0915)	(0.202)
FTK(t-5)* EXP (t-1)	0.0289	0.0575	0.0134	0.0107
	(0.0751)	(0.142)	(0.0837)	(0.141)
FTK(t-5)	-0.399	-0.575	-0.583	-0.705
	(0.463)	(0.849)	(0.625)	(1.396)
N	894	894	894	894

Notes: All the models include continent dummies, linear and squared time trends, with robust standard errors clustered at the country level. Open and Experience variables are demeaned when being interacted with the foreign knowledge stock variables. Regressions in panel B and C include all the other controls variables.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix
Appendix 1. Patent Search Codes

In search of the quake-proof building patents, I used the following code on *delphion.com*:

((E04H 00902) <in> IC).

E04H 00902 - Buildings, groups of buildings, or shelters, adapted to withstand or provide protection against, abnormal external influences (e.g. war-like action, earthquake, extreme climate) withstanding earthquake or sinking of ground.

Appendix 2. Measurement of foreign knowledge: Weighting foreign patents

To construct the foreign knowledge stocks, I first identify the number of foreign patents external to a country in a given year, and apply it in the equation (5). Because the inherent values of patents vary substantially across countries, I follow Popp et al. (2011) by weighting each patent by its family size and including only those that are filed in multiple countries.[59] More specifically, to investigate the impact of global technological change on investment in renewable energy capacity, Popp et al. (2011) developed four alternative methods for counting patents: 1) no weighting for an indivudal patent and counting each patent family as one invention; 2) no weighting but only including inventions for which patents are filed in multiple countries; 3) weighting each patent by its family size; and 4) weighting patents by family size and only including inventions for which patents are filed in multiple countries. They find that using the last method generally leads to the best fit of the model.

One issue is about dealing with patents filed with the European Patent Office (EPO), which gives inventors patent protections in multiple European countries at lower costs compared to filing through individual-country patent offices. Also based on Popp et al. (2011), I treat EPO as a single entity, but give more weights to patents filed through the EPO. Specifically, patents that are firstly filed through the EPO receive a weight of at least two: one for the home country, and a second for the EPO application (they will receive more credits if these patents are filed in countries outside Europe). For patents that are not initially filed in Europe, an EPO duplicate they receive is counted twice, while they receive a maximum of two credits for filing in multiple EPO member states instead of EPO. Finally, for patents that are initially filed in an EPO country but not with the EPO,

[59] A patent family refers to the patent filings for the same invention in different countries. It is widely regarded that inventors tend to file patents for their most valuable and potentially profitable inventions in multiple countries, which makes the size of patent family a proxy for the quality of individual patents.

all duplicate patent filings in any EPO country are counted as a single family member.

Appendix 3. Examination of missing data

To investigate the potential causes of missing data on earthquake losses, I create a binary variable indicating whether an earthquake event has missing deaths or damage, and then I regress this variable on all my independent variables (including event-specific and country-specific characteristics) using a probit model. Columns 1 and 2 report the regression results with the dependent variable on missing deaths, while Columns 3 and 4 report the results of the dependent variable on missing monetary damages. For both measures, I run the regression on the full sample (all earthquake events of all magnitudes), and my final sample (earthquakes that are above 5 on the Richter scale). The estimation results for both deaths and damages indicate that smaller-magnitude earthquakes that occurred more deeply in the crust, and also in less populated areas, are more likely to have missing values. Moreover, the probability of missing deaths also correlates with a country's political right, health condition and domestic knowledge. As discussed in the main paper, this result could be largely driven by the earthquake events that have actually caused zero deaths/damages, but are coded as missing in the NGDC database.

Table 2-A3 Modeling the events with missing deaths and damages

	Missing on deaths		Missing on damages	
Independent variables	(1)	(2)	(3)	(4)
magnitude	-0.528***	-0.704***	-0.699***	-0.803***
	(0.0654)	(0.0930)	(0.0844)	(0.0863)
focal depth	0.00410***	0.00409***	0.00305**	0.00300**
	(0.00138)	(0.00119)	(0.00125)	(0.00121)
log(exposed population)	-0.139***	-0.161***	-0.168***	-0.183***
	(0.0363)	(0.0423)	(0.0415)	(0.0448)
log(GDP per capital) (t-1)	0.244	0.840	0.173	0.334
	(1.014)	(1.074)	(1.074)	(1.126)
$[\log(\text{GDP per capital})]^2$(t-1)	-0.0214	-0.0596	-0.0182	-0.0303
	(0.0618)	(0.0650)	(0.0646)	(0.0685)
political rights(t-1)	-0.0765*	-0.0875*	-0.0237	-0.0237
	(0.0394)	(0.0471)	(0.0384)	(0.0447)
log(population)(t-1)	-0.0336	-0.114	0.0208	0.000561
	(0.103)	(0.115)	(0.145)	(0.147)
urban (t-1)	-0.00535	-0.00548	0.00429	0.00741
	(0.00511)	(0.00548)	(0.00663)	(0.00671)
health (t-1)	-0.0927***	-0.0944***		
	(0.0318)	(0.0350)		
open (t-1)	-0.00356	-0.00255	-0.00300	-0.00638
	(0.00647)	(0.00724)	(0.00619)	(0.00696)
log(patent applications) (t-1)	-0.0323	-0.0381	-0.0126	-0.0194
	(0.0377)	(0.0421)	(0.0361)	(0.0356)
log(area)	-0.0186	0.0431	-0.151	-0.140
	(0.0804)	(0.0914)	(0.103)	(0.110)
EXP(t-1)	-0.00952	0.0697	0.120	0.217**
	(0.0747)	(0.0801)	(0.0875)	(0.0949)
TK(t-1)	0.0914*	0.156***	-0.0167	-0.00735
	(0.0482)	(0.0453)	(0.0534)	(0.0584)
Constant	6.689	6.638	8.881*	9.639*
	(4.520)	(4.851)	(5.328)	(5.467)
Magnitude	all	>=5	all	>=5
Observations	1,095	894	1,095	894

Notes: All the models include continent dummies, year fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 4. Estimating the impact of knowledge on smaller-magnitude earthquakes

Given that earthquakes below magnitude 5 usually result in very minor damages, we may expect that both technical knowledge and past experience play a limited role in mitigating the impacts of these events. To investigate this issue, I estimate separate coefficients on knowledge measures for earthquakes below 5 and earthquakes that measure 5 and above on the Richter scale. Specifically, I create two binary variables: one variable equals one if an earthquake is below 5 and zero otherwise, and the other variable equaling one if an earthquake is 5 and above and zero otherwise. I interact both two variables with the technical knowledge and experience stocks, respectively. Columns 1-4 report the results using earthquake fatalities' as the outcome variable, while column 5 indicates monetary damages. The estimation results generally indicate that neither technical knowledge nor experience has a significant impact on the losses caused by smaller earthquakes, while their mitigating effects are more pronounced for larger ones.

Table 2-A4 Testing the differential effect of knowledge on earthquakes of different scales

Dependent variables	Fatalities				Damages
	(1)	(2)	(3)	(4)	(5)
Independent variables	OLS	Tobit	Censored Normal	Selection	Selection
EXP(t-1)*quakes 5+	-0.284***	-0.249	-0.290**	-0.357	-1.322**
	(0.0934)	(0.178)	(0.120)	(0.303)	(0.609)
EXP(t-1)*quakes 5-	-0.140	-0.0807	-0.0818	-0.0887	0.470
	(0.114)	(0.254)	(0.184)	(0.413)	(0.841)
TK(t-1)* quakes 5+	-0.135**	-0.265**	-0.155**	-0.322	0.179
	(0.0553)	(0.112)	(0.0788)	(0.212)	(0.290)
TK(t-1)* quakes 5-	0.0430	0.0364	0.0622	-0.0190	-0.539
	(0.103)	(0.288)	(0.192)	(0.365)	(0.642)
magnitude	1.061***	1.986***	1.493***	2.674***	3.637***
	(0.153)	(0.201)	(0.185)	(0.531)	(1.069)
focal depth	-0.00356***	-0.0133***	-0.00963***	-0.0166***	-0.0220**
	(0.00108)	(0.00418)	(0.00263)	(0.00582)	(0.0103)
log(exposed population)	0.134***	0.445***	0.305***	0.580***	0.852***
	(0.0281)	(0.100)	(0.0653)	(0.153)	(0.264)
log(GDP per capital) (t-1)	1.223	1.604	1.865	3.006	-4.138
	(0.920)	(1.998)	(1.296)	(3.228)	(5.370)
[log(GDP per capital)]^2(t-1)	-0.0573	-0.0773	-0.0971	-0.168	0.263
	(0.0561)	(0.126)	(0.0822)	(0.197)	(0.323)
political rights(t-1)	0.0951**	0.171*	0.103	0.218*	0.347*
	(0.0440)	(0.0891)	(0.0626)	(0.132)	(0.197)
log(population)(t-1)	0.136	0.0779	0.0486	-0.00608	-0.651
	(0.131)	(0.284)	(0.194)	(0.356)	(0.496)
urban (t-1)	0.00600	0.0110	0.00552	0.0154	-0.0268
	(0.00690)	(0.0137)	(0.00990)	(0.0223)	(0.0290)
health (t-1)	0.101***	0.199***	0.119***	0.246**	
	(0.0368)	(0.0620)	(0.0407)	(0.116)	
open (t-1)	-0.0101*	-0.00914	-0.0133	-0.0206	-0.0481
	(0.00599)	(0.0151)	(0.00913)	(0.0209)	(0.0371)
log(patent applications) (t-1)	0.000715	0.0578	0.0198	0.101	0.110
	(0.0415)	(0.0892)	(0.0552)	(0.137)	(0.210)
log(area)	-0.0184	0.0977	0.0853	0.123	0.157
	(0.124)	(0.234)	(0.176)	(0.298)	(0.470)
Constant	-16.31***	-32.07***	-24.85***	-44.94***	-12.73
	(4.477)	(8.938)	(5.706)	(16.41)	(27.92)
N	1095	1095	1095	1095	1095

Notes: All the models include continent dummies, year fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 5 Further checks on experience stocks

As discussed in the main paper, the previous literature often uses the cumulative counts of or average disaster frequency to characterize a country's disaster risk and model the "learning-by-doing" effect. I construct a time-varying measure of the experience stocks, which puts more weights on more recent earthquake events. To test their individual explanatory power, I also create a similar frequency measure by counting the number of 5+ earthquakes that occurred in a country during the period 1960-2010, and include both the experience stocks and frequency variables in the same regression. Table 2-A5a, columns 1-4 report the results using earthquake fatalities' as the outcome variable, while column 5 indicates monetary damages. I find that none of the frequency variables are statistically significant across all specifications. By contrast, most of the experience stocks are still significant (suggesting their stronger explanatory power), although their significance declines because of the high correlation with the frequency measures.

As another robustness check, I use the earthquakes that measure 6 and above on the Richter scale to calculate the experience stocks. This variable is consistently significant across all specifications for explaining earthquake fatalities and damages, as shown in Table 2-A5b.

Table 2-A5a Testing the explanatory power of experiences stocks *vs* a frequency measure

Dependent variables	Fatalities				Damages
Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection	(5) Selection
EXP (t-1)	-0.433**	-0.527	-0.524*	-0.622*	-1.849**
	(0.195)	(0.395)	(0.274)	(0.370)	(0.828)
Frequency(t-1)	0.00183	0.00148	0.00225	0.000939	0.0238
	(0.00490)	(0.00965)	(0.00669)	(0.00715)	(0.0150)
TK (t-1)	-0.176***	-0.349***	-0.203**	-0.320*	-0.0613
	(0.0649)	(0.115)	(0.0860)	(0.163)	(0.218)
magnitude	1.275***	2.354***	1.791***	2.706***	3.147***
	(0.173)	(0.223)	(0.207)	(0.426)	(0.817)
focal depth	-0.00338***	-0.0125***	-0.00924***	-0.0130***	-0.0173**
	(0.00107)	(0.00367)	(0.00243)	(0.00398)	(0.00793)
log(exposed population)	0.156***	0.503***	0.355***	0.537***	0.755***
	(0.0305)	(0.121)	(0.0841)	(0.117)	(0.207)
log(GDP per capital) (t-1)	1.285	1.068	1.854	2.509	-2.220
	(1.180)	(2.122)	(1.452)	(2.432)	(4.420)
[log(GDP per capital)]^2(t-1)	-0.0566	-0.0376	-0.0926	-0.132	0.146
	(0.0715)	(0.133)	(0.0913)	(0.149)	(0.267)
political rights(t-1)	0.125**	0.208**	0.135**	0.238**	0.275
	(0.0505)	(0.0926)	(0.0662)	(0.104)	(0.171)
log(population)(t-1)	0.204	0.231	0.122	0.146	-0.658*
	(0.151)	(0.297)	(0.206)	(0.268)	(0.395)
urban (t-1)	0.00409	0.00811	0.00386	0.00817	-0.0313
	(0.00826)	(0.0144)	(0.0106)	(0.0165)	(0.0231)
health (t-1)	0.0993*	0.185**	0.112*	0.172**	
	(0.0525)	(0.0800)	(0.0576)	(0.0866)	
open (t-1)	-0.0147**	-0.0109	-0.0155	-0.0244	-0.0535*
	(0.00677)	(0.0156)	(0.00983)	(0.0162)	(0.0285)
log(patent applications) (t-1)	0.0152	0.0668	0.0329	0.0743	0.245
	(0.0460)	(0.0881)	(0.0557)	(0.103)	(0.166)
log(area)	-0.0831	0.0103	0.0363	-0.0105	-0.159
	(0.161)	(0.260)	(0.201)	(0.226)	(0.348)
Constant	-19.90***	-36.64***	-29.82***	-43.88***	-13.57
	(5.547)	(10.07)	(6.912)	(12.10)	(23.06)
Left censored		465	465		
N	894	894	894	894	894

Notes: All the models include continent dummies, year fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-A5b Robustness Check – using experiences stock based on 6+ earthquakes

Dependent variables	Fatalities				Damages
Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection	(5) Selection
EXP (t-1)	-0.537***	-0.757***	-0.664***	-0.951***	-1.393**
	(0.113)	(0.188)	(0.127)	(0.284)	(0.545)
TK (t-1)	-0.130**	-0.282**	-0.143*	-0.272	0.0810
	(0.0622)	(0.113)	(0.0819)	(0.185)	(0.244)
magnitude	1.323***	2.418***	1.850***	2.922***	3.379***
	(0.178)	(0.219)	(0.205)	(0.495)	(0.905)
focal depth	-0.00323***	-0.0118***	-0.00867***	-0.0129***	-0.0190**
	(0.00105)	(0.00340)	(0.00221)	(0.00444)	(0.00834)
log(exposed population)	0.154***	0.493***	0.345***	0.563***	0.776***
	(0.0294)	(0.116)	(0.0795)	(0.133)	(0.217)
log(GDP per capital) (t-1)	1.478	1.496	2.171	3.062	-4.007
	(1.096)	(1.965)	(1.343)	(2.728)	(4.482)
[log(GDP per capital)]^2(t-1)	-0.0712	-0.0671	-0.115	-0.170	0.267
	(0.0676)	(0.127)	(0.0867)	(0.167)	(0.270)
political rights(t-1)	0.0901	0.157	0.0956	0.186	0.351**
	(0.0575)	(0.110)	(0.0785)	(0.113)	(0.164)
log(population)(t-1)	0.226	0.277	0.166	0.246	-0.500
	(0.147)	(0.289)	(0.201)	(0.305)	(0.417)
urban (t-1)	0.00554	0.0110	0.00623	0.0148	-0.0357
	(0.00765)	(0.0139)	(0.0101)	(0.0182)	(0.0244)
health (t-1)	0.0853**	0.169***	0.0974**	0.179*	
	(0.0411)	(0.0646)	(0.0439)	(0.0928)	
open (t-1)	-0.0148**	-0.0102	-0.0147	-0.0216	-0.0357
	(0.00653)	(0.0152)	(0.00949)	(0.0183)	(0.0309)
log(patent applications) (t-1)	-0.0179	0.0199	-0.0101	0.0302	0.134
	(0.0466)	(0.0855)	(0.0528)	(0.116)	(0.173)
log(area)	-0.0533	0.0476	0.0642	0.0133	-0.0355
	(0.150)	(0.252)	(0.194)	(0.250)	(0.384)
Constant	-19.51***	-37.50***	-29.91***	-47.27***	-7.743
	(4.984)	(8.463)	(5.647)	(13.88)	(22.78)
Left censored		465	465		
N	894	894	894	894	894

Notes: All the models include continent dummies, year fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 6. Test of income without including the knowledge stocks

As discussed in the main paper, most of the prior empirical studies have found that income is an important determinant of disaster losses. One contribution of this research is to examine the role of technology development in disaster mitigation and I find that the income variables are statistically insignificant with the inclusion of the variable capturing a country's accumulation of technical innovations for earthquake mitigation. In Table 2-A6, I dropped the technical knowledge variable and re-ran the same regressions. I find that without controlling for technology, the income variables, including the logged GDP per capita and its quadratic term, both become significant, and the pattern of the income-disaster relationship, as suggested by the signs of the estimated coefficients, are consistent with the findings in Kellenberg and Mobarak (2008). Specifically, they find that that disaster-related fatalities do not decrease monotonically with income. They argue for a non-linear relationship between disaster impacts and wealth, because economic development can result in competing influences on disaster risks (i.e., people at lower-income levels may favor consumption over risk reduction). Combining the results in Table 2-3, this research shows that the inclusion of knowledge stock lowers the predictive power of income for earthquake fatalities, and furthermore, it suggests that an important mechanism that higher income reduces disaster impacts is because it enables more resources devoted to the development of technical knowledge.

Table 2-A6 Modeling earthquake fatalities without including domestic knowledge stocks

Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection
EXP (t-1)	-0.384***	-0.486**	-0.442***	-0.582***
	(0.110)	(0.186)	(0.133)	(0.229)
magnitude	1.240***	2.298***	1.760***	2.556***
	(0.173)	(0.221)	(0.205)	(0.359)
focal depth	-0.00373***	-0.0133***	-0.00969***	-0.0132***
	(0.00110)	(0.00403)	(0.00263)	(0.00363)
log(exposed population)	0.157***	0.509***	0.357***	0.513***
	(0.0306)	(0.120)	(0.0829)	(0.103)
log(GDP per capital) (t-1)	2.797**	4.160**	3.563***	5.191***
	(1.172)	(2.071)	(1.352)	(1.848)
[log(GDP per capital)]^2(t-1)	-0.151**	-0.232*	-0.200**	-0.302***
	(0.0713)	(0.132)	(0.0853)	(0.111)
political rights(t-1)	0.115*	0.181*	0.125	0.199**
	(0.0583)	(0.106)	(0.0760)	(0.0857)
log(population)(t-1)	0.211	0.243	0.135	0.144
	(0.157)	(0.305)	(0.213)	(0.240)
urban (t-1)	0.00652	0.0133	0.00599	0.0123
	(0.00785)	(0.0146)	(0.0106)	(0.0146)
health (t-1)	0.0994**	0.191***	0.110**	0.169**
	(0.0458)	(0.0695)	(0.0490)	(0.0757)
open (t-1)	-0.0148**	-0.0116	-0.0159	-0.0252*
	(0.00746)	(0.0166)	(0.0104)	(0.0145)
log(patent applications) (t-1)	-0.0627	-0.0783	-0.0544	-0.0502
	(0.0413)	(0.0775)	(0.0476)	(0.0735)
log(area)	-0.0466	0.0467	0.0579	0.0183
	(0.159)	(0.268)	(0.205)	(0.201)
Constant	-24.36***	-47.10***	-34.68***	-50.05***
	(5.320)	(8.822)	(6.077)	(11.10)
Left censored		465	465	
N	894	894	894	894

Notes: All the models include continent fixed effects, year fixed effects, with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 7 Sensitivity test of the foreign knowledge stocks lagged by different years

In Table 2-6, I report the estimation results using 5-year lagged foreign knowledge stocks. Because of the length of time it may take technical innovations to diffuse to other countries is unknown, I perform a set of sensitivity tests using 3-year and 10-year lagged foreign knowledge, respectively. As shown in Tables 2-A7a and 2-A7b, neither of the lagged foreign knowledge stocks is statistically significant for explaining domestic fatalities.

Table 2-A7a Using three-year lagged foreign knowledge stocks

Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection
EXP (t-1)	-0.337***	-0.413**	-0.378***	-0.504*
	(0.107)	(0.189)	(0.136)	(0.279)
TK (t-1)	-0.221***	-0.416***	-0.268***	-0.463**
	(0.0750)	(0.118)	(0.0975)	(0.212)
FTK(t-5)	-0.598	-1.022	-1.057	-1.442
	(0.625)	(1.028)	(0.770)	(1.818)
magnitude	1.262***	2.320***	1.758***	2.850***
	(0.177)	(0.244)	(0.221)	(0.524)
focal depth	-0.00328***	-0.0120***	-0.00912***	-0.0145***
	(0.00109)	(0.00397)	(0.00260)	(0.00469)
log(exposed population)	0.155***	0.483***	0.337***	0.591***
	(0.0304)	(0.122)	(0.0833)	(0.148)
log(GDP per capital) (t-1)	1.353	1.356	1.940	2.608
	(1.188)	(2.097)	(1.470)	(2.809)
[log(GDP per capital)]^2(t-1)	-0.0586	-0.0520	-0.0970	-0.134
	(0.0719)	(0.132)	(0.0921)	(0.173)
political rights(t-1)	0.154***	0.253**	0.164**	0.293**
	(0.0561)	(0.0983)	(0.0725)	(0.126)
log(population)(t-1)	0.226	0.291	0.153	0.257
	(0.156)	(0.312)	(0.218)	(0.321)
urban (t-1)	0.00431	0.00975	0.00379	0.0110
	(0.00777)	(0.0139)	(0.0103)	(0.0192)
health (t-1)	0.109**	0.202***	0.121**	0.221**
	(0.0441)	(0.0696)	(0.0503)	(0.104)
open (t-1)	-0.0136**	-0.00914	-0.0152	-0.0214
	(0.00641)	(0.0144)	(0.00932)	(0.0189)
log(patent applications) (t-1)	0.0265	0.0867	0.0492	0.111
	(0.0503)	(0.0977)	(0.0604)	(0.120)
log(area)	-0.0898	-0.0281	0.0209	-0.0515
	(0.157)	(0.276)	(0.211)	(0.266)
time trend	0.134	0.238	0.226	0.311
	(0.155)	(0.255)	(0.193)	(0.450)
time trend^2	-0.00213	-0.00458	-0.00356	-0.00535
	(0.00274)	(0.00453)	(0.00345)	(0.00779)
Constant	-17.61***	-33.95***	-25.30***	-42.35***
	(5.257)	(9.298)	(6.693)	(15.20)
N	894	894	894	894

Notes: All the models include continent fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-A7b Using ten-year lagged foreign knowledge stocks

	(1)	(2)	(3)	(4)
Independent variables	**OLS**	**Tobit**	**Censored Normal**	**Selection**
EXP (t-1)	-0.304***	-0.357**	-0.326**	-0.464
	(0.104)	(0.178)	(0.132)	(0.346)
TK (t-1)	-0.200***	-0.380***	-0.229***	-0.468*
	(0.0588)	(0.120)	(0.0837)	(0.251)
FTK(t-5)	0.0904	-0.0813	0.289	0.0679
	(0.310)	(0.514)	(0.397)	(1.112)
magnitude	1.254***	2.366***	1.787***	3.134***
	(0.175)	(0.274)	(0.233)	(0.699)
focal depth	-0.00317***	-0.0120***	-0.00900***	-0.0153***
	(0.00108)	(0.00416)	(0.00270)	(0.00576)
log(exposed population)	0.158***	0.525***	0.364***	0.706***
	(0.0320)	(0.149)	(0.102)	(0.210)
log(GDP per capital) (t-1)	1.531	1.855	2.190	3.105
	(1.114)	(2.175)	(1.447)	(3.548)
[log(GDP per capital)]^2(t-1)	-0.0737	-0.0818	-0.114	-0.162
	(0.0682)	(0.136)	(0.0908)	(0.215)
political rights(t-1)	0.132**	0.218**	0.134*	0.287*
	(0.0536)	(0.0975)	(0.0722)	(0.155)
log(population)(t-1)	0.223	0.286	0.104	0.259
	(0.148)	(0.307)	(0.214)	(0.415)
urban (t-1)	0.00463	0.00700	0.00111	0.00889
	(0.00822)	(0.0154)	(0.0119)	(0.0245)
health (t-1)	0.106***	0.215***	0.121***	0.264*
	(0.0382)	(0.0647)	(0.0448)	(0.154)
open (t-1)	-0.0148**	-0.0107	-0.0181*	-0.0233
	(0.00685)	(0.0151)	(0.0103)	(0.0239)
log(patent applications) (t-1)	0.0497	0.110	0.0883	0.178
	(0.0452)	(0.0994)	(0.0591)	(0.156)
log(area)	-0.138	-0.0784	-0.0254	-0.148
	(0.156)	(0.285)	(0.220)	(0.336)
time trend	-7.72e-05	0.103	-0.0734	0.0396
	(0.139)	(0.219)	(0.179)	(0.493)
time trend^2	-0.000312	-0.00293	0.000814	-0.00180
	(0.00257)	(0.00403)	(0.00331)	(0.00890)
Constant	-19.60***	-39.95***	-29.24***	-53.13***
	(5.028)	(10.52)	(7.100)	(19.97)
N	806	806	806	806

Notes: All the models include continent fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Appendix 8 Examining the global trend in earthquake losses

Instead of limiting foreign knowledge to a specific type of technology, here I test whether there has been a significant global decrease in earthquake-related losses over time, considering the gradual improvement of knowledge of coping with earthquakes. Therefore, I re-run the same regressions by replacing the year fixed effects with a time trend (in Table 2-A8a) and quadratic time trends (Table 2-A8b). However, my results do not provide strong evidence on the downward global trend in earthquake fatalities and damages, since the estimated coefficients on time variables are all statistically insignificant across all specifications. To allow for the differential trends in developed *versus* developing countries, I interact the time trend with developing and developing country dummies, respectively. As shown in Table 2-A8c, the interaction terms are also statistically insignificant, suggesting no differences between the two country groups.

Table 2-A8a Replace year fixed effects with a simple time trend

Dependent variables	Fatalities				Damages
	(1)	(2)	(3)	(4)	(5)
Independent variables	OLS	Tobit	Censored Normal	Selection	Selection
EXP (t-1)	-0.329***	-0.423**	-0.360***	-0.479*	-1.095**
	(0.104)	(0.181)	(0.128)	(0.287)	(0.483)
TK (t-1)	-0.197***	-0.371***	-0.229***	-0.415**	-0.0727
	(0.0610)	(0.115)	(0.0817)	(0.203)	(0.220)
magnitude	1.265***	2.335***	1.762***	2.926***	3.388***
	(0.177)	(0.246)	(0.225)	(0.550)	(0.904)
focal depth	-0.00325***	-0.0118***	-0.00898***	-0.0148***	-0.0179**
	(0.00108)	(0.00394)	(0.00256)	(0.00487)	(0.00845)
log(exposed population)	0.155***	0.483***	0.334***	0.604***	0.765***
	(0.0301)	(0.122)	(0.0830)	(0.154)	(0.220)
log(GDP per capital) (t-1)	1.257	1.266	1.713	2.241	-2.160
	(1.214)	(2.075)	(1.521)	(2.911)	(4.210)
[log(GDP per capital)]^2(t-1)	-0.0512	-0.0441	-0.0790	-0.106	0.175
	(0.0740)	(0.131)	(0.0956)	(0.178)	(0.253)
political rights(t-1)	0.150***	0.251***	0.158**	0.292**	0.380**
	(0.0550)	(0.0959)	(0.0721)	(0.132)	(0.156)
log(population)(t-1)	0.228	0.291	0.155	0.257	-0.401
	(0.156)	(0.312)	(0.219)	(0.335)	(0.403)
urban (t-1)	0.00422	0.00942	0.00305	0.0101	-0.0431*
	(0.00785)	(0.0140)	(0.0105)	(0.0201)	(0.0244)
health (t-1)	0.112**	0.204***	0.129**	0.237**	
	(0.0436)	(0.0681)	(0.0504)	(0.105)	
open (t-1)	-0.0136**	-0.00997	-0.0145	-0.0198	-0.0401
	(0.00644)	(0.0139)	(0.00907)	(0.0193)	(0.0286)
log(patent applications) (t-1)	0.0238	0.0820	0.0450	0.108	0.149
	(0.0495)	(0.0974)	(0.0609)	(0.126)	(0.169)
log(area)	-0.0994	-0.0391	0.00772	-0.0561	-0.0898
	(0.156)	(0.274)	(0.212)	(0.278)	(0.371)
t	-0.00200	-0.0248	-0.00731	-0.0264	-0.0747
	(0.00860)	(0.0179)	(0.0121)	(0.0258)	(0.0738)
Constant	-19.14***	-36.67***	-27.89***	-46.60***	-17.39
	(5.258)	(9.258)	(6.650)	(15.27)	(23.25)
Left censored	0	465	465		
N	894	894	894	894	894

Notes: All the models include continent fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-A8b Replace year fixed effects with linear and squared time trend

Dependent variables	Fatalities				Damages
	(1)	(2)	(3)	(4)	(5)
Independent variables	OLS	Tobit	Censored Normal	Selection	Selection
EXP (t-1)	-0.335***	-0.413**	-0.378***	-0.505*	-1.088**
	(0.107)	(0.189)	(0.137)	(0.276)	(0.462)
TK (t-1)	-0.195***	-0.373***	-0.226***	-0.408**	-0.0740
	(0.0604)	(0.115)	(0.0827)	(0.196)	(0.213)
magnitude	1.268***	2.331***	1.770***	2.860***	3.322***
	(0.179)	(0.246)	(0.224)	(0.520)	(0.884)
focal depth	-0.00325***	-0.0119***	-0.00895***	-0.0142***	-0.0181**
	(0.00109)	(0.00393)	(0.00255)	(0.00464)	(0.00814)
log(exposed population)	0.155***	0.482***	0.335***	0.585***	0.751***
	(0.0302)	(0.122)	(0.0829)	(0.147)	(0.216)
log(GDP per capital) (t-1)	1.287	1.221	1.792	2.399	-2.178
	(1.192)	(2.090)	(1.492)	(2.774)	(4.072)
$[\log(\text{GDP per capital})]^2$(t-1)	-0.0533	-0.0407	-0.0847	-0.116	0.175
	(0.0725)	(0.132)	(0.0940)	(0.170)	(0.246)
political rights(t-1)	0.151***	0.249**	0.161**	0.289**	0.374**
	(0.0558)	(0.0974)	(0.0720)	(0.124)	(0.150)
log(population)(t-1)	0.227	0.292	0.154	0.255	-0.401
	(0.156)	(0.311)	(0.217)	(0.318)	(0.388)
urban (t-1)	0.00428	0.00933	0.00322	0.00954	-0.0428*
	(0.00782)	(0.0140)	(0.0105)	(0.0190)	(0.0237)
health (t-1)	0.111**	0.206***	0.125**	0.225**	
	(0.0446)	(0.0705)	(0.0518)	(0.103)	
open (t-1)	-0.0139**	-0.00943	-0.0155*	-0.0217	-0.0411
	(0.00635)	(0.0143)	(0.00924)	(0.0187)	(0.0281)
log(patent applications) (t-1)	0.0235	0.0822	0.0446	0.106	0.147
	(0.0495)	(0.0978)	(0.0601)	(0.119)	(0.163)
log(area)	-0.0987	-0.0402	0.00892	-0.0633	-0.0991
	(0.156)	(0.274)	(0.210)	(0.263)	(0.361)
t	-0.0118	-0.0105	-0.0313	-0.0407	-0.0867
	(0.0358)	(0.0528)	(0.0424)	(0.0767)	(0.0973)
t^2	0.000293	-0.000434	0.000729	0.000553	0.000646
	(0.00104)	(0.00166)	(0.00131)	(0.00234)	(0.00292)
Constant	-19.19***	-36.60***	-28.02***	-45.88***	-16.22
	(5.238)	(9.277)	(6.544)	(14.46)	(22.45)
Left censored		465	465		
N	894	894	894	894	894

Notes: All the models include continent fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2-A8c Interact time trend with developed and developing nation dummies

Dependent variables	Fatalities				Damages
Independent variables	(1) OLS	(2) Tobit	(3) Censored Normal	(4) Selection	(5) Selection
EXP (t-1)	-0.329***	-0.422**	-0.360***	-0.481*	-1.103**
	(0.105)	(0.182)	(0.128)	(0.286)	(0.496)
TK (t-1)	-0.198***	-0.373***	-0.229***	-0.411**	-0.0766
	(0.0608)	(0.115)	(0.0819)	(0.205)	(0.229)
magnitude	1.265***	2.335***	1.762***	2.921***	3.420***
	(0.177)	(0.246)	(0.225)	(0.547)	(0.947)
focal depth	-0.00324***	-0.0119***	-0.00898***	-0.0147***	-0.0180**
	(0.00109)	(0.00389)	(0.00253)	(0.00485)	(0.00875)
log(exposed population)	0.155***	0.483***	0.334***	0.602***	0.774***
	(0.0302)	(0.123)	(0.0838)	(0.153)	(0.229)
log(GDP per capital) (t-1)	1.328	1.358	1.721	2.098	-2.091
	(1.468)	(2.421)	(1.803)	(3.282)	(5.241)
[log(GDP per capital)]^2(t-1)	-0.0559	-0.0502	-0.0796	-0.0960	0.172
	(0.0908)	(0.154)	(0.115)	(0.206)	(0.322)
political rights(t-1)	0.150***	0.251***	0.158**	0.292**	0.377**
	(0.0550)	(0.0961)	(0.0721)	(0.131)	(0.160)
log(population)(t-1)	0.228	0.291	0.155	0.256	-0.404
	(0.156)	(0.312)	(0.219)	(0.333)	(0.415)
urban (t-1)	0.00433	0.00963	0.00307	0.00981	-0.0435*
	(0.00803)	(0.0143)	(0.0109)	(0.0204)	(0.0254)
health (t-1)	0.112**	0.204***	0.129**	0.237**	
	(0.0437)	(0.0680)	(0.0505)	(0.104)	
open (t-1)	-0.0135**	-0.00985	-0.0145	-0.0199	-0.0392
	(0.00658)	(0.0141)	(0.00930)	(0.0195)	(0.0298)
log(patent applications) (t-1)	0.0240	0.0825	0.0450	0.107	0.147
	(0.0491)	(0.0966)	(0.0605)	(0.125)	(0.176)
log(area)	-0.0987	-0.0380	0.00785	-0.0565	-0.0735
	(0.156)	(0.275)	(0.213)	(0.278)	(0.382)
Developing*t	-0.00231	-0.0252	-0.00735	-0.0257	-0.0773
	(0.0100)	(0.0206)	(0.0138)	(0.0266)	(0.0844)
Developed*t	-0.000697	-0.0227	-0.00710	-0.0292	-0.0758
	(0.0103)	(0.0203)	(0.0157)	(0.0467)	(0.0773)
Constant	-19.40***	-37.02***	-27.92***	-45.97***	-18.31
	(6.221)	(11.05)	(8.035)	(16.30)	(29.01)
Left censored		465	465		
N	894	894	894	894	894

Notes: All the models include continent fixed effects and are estimated with robust standard errors clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3: What Drives Climate Preparedness: An Assessment of State Climate Adaptation Planning in the United States

1. Introduction

There is a growing consensus that climate change is taking place and posing unevenly distributed risks across regions and sectors. The risks, as warned by climate scientists, include not only long-term changes, such as higher temperature and sea level rise, but also greater climate variability and more frequent and intense extreme events, including tropical cycles, floods, severe storms, droughts and heat waves. Effectively addressing climate change requires adaptation, which encompasses a wide range of actions individuals, firms and governments take to reduce the adverse climate impacts or exploit beneficial opportunities (Tompkins and Eakin, 2012; IPCC, 2007; Smit et al., 1999; Fankhauser et al., 1999).[60] While some adaptation occurs autonomously (e.g., migration from regions at high risk of climate change), other adaptation requires greater foresight and planning (e.g., building preventive infrastructure to accommodate sea level rise), and therefore, is purposive and policy-driven (Stern, 2006). In recent years, states and localities have started making plans to prepare their communities for climate change in the absence of a federal climate policy.

In this paper, I investigate the factors that lead U.S. state governments to engage in formal planning for climate change adaptation. Fussel (2007:268) characterizes adaptation planning as "… the use of information about present and future climate change to review the suitability of current and planned practices, policies and infrastructures." From a policy process perspective, making an adaptation plan represents the first step in undertaking systematic actions to build long-

[60] Adaptation is formally defined by the International Panel on Climate Change (IPCC) as "*adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploit beneficial opportunities*" (IPCC, 2001: 72).

term climate preparedness. The plan articulates the adaptation policy by assessing climate risks and identifying principles, strategies and recommendations. Moreover, usually formulated through a participatory decision-making process, adaptation plans facilitate consensus building on key issues and solutions, and improves communication between public officials and stakeholders, thereby leading to more coordinated decisions and actions. They also help legitimize and institutionalize climate adaptation on states' political agenda, by providing an "ongoing framework" for governments to identify and implement strategies and evaluate progress (Wheeler, 2008).

Recent years have witnessed the rapid development of adaptation plans at all levels of government across the world, accompanied by an emerging body of research on adaptation planning. Studies have mostly focused on tracking the progress of adaptation planning (e.g., Bieraum et al., 2013; Cruce, 2009; Carmin et al., 2012a; Preston et al., 2011a; Lesnikowski et al., 2013; Berrang-Ford et al., 2011; Ford et al., 2011), evaluating plan documents (Preston et al., 2011b; Preston et al., 2009; Baker et al., 2012; Chou et al., 2012; Wilson, 2006), proposing approaches and principles (Fussel, 2007, Philip Berke and Lyles, 2012), linking scientific research with planning decisions (Mastrandrwa et al., 2010; Larsen et al., 2012; Moser, 2010), and examining adaptation planning more specifically in urban and local contexts (Carmin et al., 2012b; Anguelovski and Carmin, 2011; Hunt and Watkiss, 2011; Berrang-Ford et al., 2014; Measham et al., 2011).

This research takes a new angle by examining the factors that may have influenced the development of statewide adaptation plans through a policy innovation lens. From a research point of view, understanding the determinants of plan development provides the foundation necessary for assessing the effects of these plans on improving climate resilience. More importantly, this paper advances our understanding of subnational adaptation policy-making in four ways. First, while the extant literature often discuss barriers to undertaking climate adaptations (e.g., limited resources and lack of information), it devotes much less attention to the motivation for adaptation and therefore, does not fully explain why adaptation occurs in some communities but not the others. This paper fills this gap by incorporating both motivation and capacity factors to account for the state-level decision to pursue adaptation planning.

Second, this paper adds to a growing literature that seeks to explain state and local adoption of climate policies, which, to date, has predominantly dealt with reducing greenhouse gas (GHG) emissions (e.g., Rabe, 2004; Lyon and Yin, 2010, Brody et al., 2008). Although mitigation and adaptation are both recognized as important strategies to combat climate change, the problems they address are different in nature and in scope. Unlike mitigation which provides a global public good with non-excludable benefits, adaptation is mostly local and provides local benefits given the spatial variation of climate impacts. This naturally puts states and localities on the frontline of climate adaptation, and implies distinct drivers of adaptation policy making at the subnational level from that of mitigation. This paper is the first of its kind to explain the development of adaptation plans at the state level.

Third, examining the drivers of state-level adaptation decisions contributes to the existing literature on environmental federalism (Oates, 2001). Because decentralization gives states the freedom to tackle local climate risks in their own ways, an essential question is whether they are effective enough, especially those most threatened by climate change. Answering this question is critical to identifying the role of the federal government in advancing national adaptations. Fourth, the practice of adaptation planning as experiments in the "laboratories of democracy" may provide important lessons to other state governments. Therefore, in this research I also consider spatial diffusion by examining whether states located within the same climate regions learn from and emulate each other in planning for climate adaptation.

Drawing upon policy innovation literature (Berry and Berry, 1990), I incorporate both state internal characteristics and spatial diffusion to explain states' decisions to undertake adaptation planning. I construct a longitudinal data set for 50 states between 2005 and 2013, and employ a discrete-time event history analysis (EHA) to model the probability that a state initiates adaptation planning in a given year. I find that the state-level adaptation decision is highly responsive to the severity of recently experienced extreme weather events, with the response varying depending on the type of hazards. This finding on reactive adaptation suggests that the federal government has an important role to play in facilitating proactive subnational adaptation. Moreover, I find that adaptation planning is closely associated with states' exposure to climate impacts, income level, civic engagement and environmental preferences. Although the results reveal rational elements in adaptation responses, the pattern of states' adaptation planning reflects inequality in their capacity and resources available to adapt, suggesting the need for more coordination and support to integrate climate adaptation and economic development.

The rest of the paper is organized as follows. Section two provides a brief overview of current status of adaptation planning in the United States. Section three provides a theoretical discussion of the factors that may have shaped the development of adaptation plans and lays out key hypotheses. I present the empirical analysis in Section four, which includes a description of the data, empirical model and my findings. Section five concludes.

2. Adaptation Planning in the United States

Climate adaptation planning is a relatively new topic for government. In the United States, the awareness and actions of adaptation lag far behind those for GHG mitigation. In a review of the first-generation U.S. state and municipal climate plans, Wheeler (2008) concludes that these plans are mostly preoccupied by GHG mitigation rather than climate adaptation. The first formal adaptation plans emerged in the U.S. in the mid-2000s, with jurisdictions using local climate projections to identify adaptation strategies in single or multi-sector settings. For a more comprehensive overview on this topic, see Bierbaum et al. (2013).

2.1 Measurement and data

To assess the current status of state adaptation planning, I collect states' planning documents using databases compiled by the Center for Climate and Energy Solutions (C2ES) and the Georgetown Climate Center, complementing the information with online searches and e-mail inquiries to the state environmental agencies.[61] I limit my analysis to the comprehensive statewide adaptation plans that address multiple major climate-sensitive sectors.[62] Additionally, the plans must be written and released by state governmental agencies, provide formal assessment of the projected climate change impacts, and explicitly identify adaptation strategies and recommendations.

As of 2013, seventeen states had completed a comprehensive adaptation plan and five states were in the process of developing plans (Figure 1). Noticeably, most of these are coastal states. This may be attributed to the increased awareness of sea level rise and their exposure to other coastal extreme events (e.g., hurricanes, coastal floods and storm surges). Additionally, these coastal states also possess many similar political and socio-economic characteristics that may lead them to take the same adaptation initiatives. Appendix 1 provides a detailed descriptive analysis of these plans (e.g., their origination process and common features). Although adaptation plans are

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[61] Appendix 1 provides more detailed descriptions of my data sources.

[62] Note that some states that have sector-specific adaptation plans are not considered here. This is because the wide-range impacts of climate change create challenges that cut across multiple sectors. For example, intense precipitation events not only affect agriculture but may also cause disruption of transportation and energy supply, and threaten public health. Therefore, multi-sector planning indicates a more coordinated and holistic approach to address adaptation.

generally nonbinding, there is evidence that most of these states are making important progress toward the goals they have set in their plans, which suggests these plans are not just symbolic.[63]

3. Conceptual Framework

3.1 Related literature

The development of an adaptation plan marks the initiation of a state's planned adaptation as well as an important change in its overall climate policy. I view adaptation planning as a policy innovation because it is a new program for the adopting government.[64] This perspective ties the study to an extensive literature that seeks to explain the adoption of new polices or policy changes by considering the internal determinants (e.g., states' political, economic and social characteristics) and spatial diffusion from other states that have previously adopted the policy. Berry and Berry (1990) first introduced this unified policy innovation model by incorporating both internal and regional factors in an EHA to explain state lottery adoptions. They have theorized three sets of conceptual factors that influence policy innovations: motivation to address a policy issue; the obstacles for policy changes; and the availability of resources to overcome the obstacles.

With a growing interest in the development of public policies, the policy innovation model has been applied to study a wide variety of environmental policies, including hazardous waste programs (Sapat, 2004), local watershed partnerships (Lubell et al., 2002), electricity sector reforms (Andrews 2000; Ka and Teske, 2002), renewable energy policies (Huang et al., 2007; Matisoff, 2008; Chandler, 2009; Lyon and Yin, 2010; Carley and Miller et al., 2012), and local

[63] The Georgetown Climate Centers has recently released a new tool that tracks state progress implementing their adaptation plans (http://www.georgetownclimate.org/adaptation/state-and-local-plans).

[64] The policy innovation literature refers to innovation as the adoption of a new policy or program by a government entity that had never utilized it before (Walker, 1969). In other words, a policy innovation is new to the adopting government, even though it might have been adopted by other governments. The concept of policy innovation is thus different from policy invention, because the latter means the development of a new policy idea.

climate actions and initiatives (Sharp et al., 2011; Zahran et al., 2008; Lubell et al., 2009). In addition to geographic variables to account for spatial diffusion, internal factors examined in these policy innovation studies generally fall into the following categories: (1) the severity of the environmental problems that prompt new policy; (2) the available resources for launching new programs; (3) political and citizen ideology; (4) characteristics of the adopting agency; and (5) characteristics of the related industries and interest groups. In addition to this line of research, one study of particular relevance is Berrang-Ford et al (2014), which links national adaptation actions with multiple determinants of adaptive capacity (e.g., income, technology, education, and institutional quality), and shows that good governance is the strongest predictor. However, their cross-sectional analysis does not take into account adoption dynamics and potential spatial diffusion of adaptation planning.

3.2 Factoring influencing the development of adaptation plans

Drawing upon the policy innovation literature, I propose four principal explanations for state-level development of adaptation plans and discuss my independent variables in each category.

3.2.1 Climate Risks

Given the nature of climate adaptation, I expect that states facing larger adverse impacts of climate change are more motivated to pursue adaptation planning. Specifically, I consider two aspects of climate risks including a state's recent extreme-weather experiences and its social vulnerability to climate impacts.

First, there is growing evidence indicating that recently-experienced extreme weather events can affect climate-change belief and perceptions, and serve as a stimuli for adaptation actions (e.g., Rudman et al. 2013; Ford et al. 2011). These findings are similar to findings from natural hazard research which suggest that natural disasters provide "windows of opportunity" for political and institutional changes, and also induce other societal responses aiming to reduce future disaster risk (e.g., Birkmann et al. 2008; Miao and Popp, 2014). These lines of research suggest an important causal relationship between recent climate experiences and adaptation decisions.

Hypothesis 1.1: States that have experienced larger losses from recent extreme weather events are more likely to undertake adaptation planning.

In addition to recent climate damages, the severity of climate risks also depends on various state internal attributes that may make states more vulnerable to the effects of climate change (e.g., Cutter et al, 2003; Adger, 2006).[65] Therefore, I consider climate vulnerability as another motivation for adaptation, and operationalize it by examining the characteristics of major climate sensitive sectors, given that a multi-sector perspective is a common feature of the statewide adaptation plans considered in this study. In particular, I consider public health, agriculture, coastal management, forestry and infrastructure, and I link each of them with specific measures of state-level attributes. First, there is a growing recognition of the health implications of climate change, especially for the elderly who are regarded as vulnerable to air pollution, heat waves and other extreme events. Thus, the public health benefits of adaptation actions might be particularly attractive to states with a large aging population.

Hypothesis 1.2: States with large proportions of the elderly are more likely to pursue adaptation planning.

[65] As an important concept in the scholarship of natural hazards and climate adaptation, vulnerability encompasses socio-economic and demographic factors to account for the propensity of local populations to be affected by extreme events and environmental change.

Among all sectors, agriculture is arguably most dependent on climate and highly sensitive to climate change and variability. Climate adaptation in agriculture sectors has important implications for crop production, livestock and the fisheries industry. Therefore, I expect adaptation planning to be especially compelling for states with a larger agricultural sector.

Hypothesis 1.3: States that are more economically dependent on agriculture are more likely to pursue adaptation planning.

Climate change is putting particular high stress on coastal regions by inducing sea-level rise, increased precipitation, more frequent and intense storms, and warmer ocean temperatures. The heavy development and population density in U.S. coastal states have also made their communities even more sensitive to these climate impacts. Therefore, their vulnerability to climate change is determined by both physical and economic exposure. Specifically, the higher the concentration of economic activities in coastal regions, the more vulnerable the entire state's economy is to the disruptions of climate change.

Hypothesis 1.4: States with longer ocean coastlines and larger shares of gross domestic product (GDP) generated from coastal areas are more likely to pursue adaptation planning.

In addition to coastal areas, climate change has also been posing risks to forest ecosystems through increased atmospheric carbon dioxide and various climate-related disturbances, including wildfires, storms, insect outbreaks and the occurrence of invasive species. The state's forest cover could be another geographic characteristic that prompts the need for adaptation.

Hypothesis 1.5: States with larger forest coverage are more likely to pursue adaptation planning.

Extreme weather events associated with climate change are increasingly threatening local infrastructure such as transportation. In this paper, I consider aging road bridges as one measure of infrastructure vulnerability and expect states with more road bridges in poor condition to have a stronger desire for adaptation planning. However, it is important to note that the problem of aging infrastructure might be rooted in a state's lack of capacity and resources to plan and invest in adaptation, which would further constrain its tendency to undertake adaptation planning. Therefore, the hypothesis that poor infrastructure is related to the probability of adaptation planning will be tested with no prediction about the direction of the relationship.

Hypothesis 1.6: A state's poor infrastructure affects its likelihood of adopting adaptation plans.

3.2.2 Adaptive capacity

In the climate change context, adaptive capacity refers to a society's capacity to undertake or overcome the obstacles to adaptation actions (IPCC, 2007). Here I consider a state's economic conditions and civic engagement as two key elements of its adaptive capacity. First, I expect a positive correlation between a state's income and its propensity for adaptation planning because higher-income states are more capable of affording adaptation measures. More affluent states may also have a higher demand for adaptation because they have more assets that could be destroyed by climate hazards.

Hypothesis 2.1: States with higher incomes are more likely to engage in adaptation planning.

Given the wide-ranging impacts of climate change on different sectors and geographic regions, adaptation is increasingly blurring the traditional boundaries between the public and the private sector, and requires the society to act collectively. In particular, adaptation planning is a collective decision-making process that heavily relies on the participation of non-governmental actors. To be consistent with the adaptive capacity literature (Adger, 2003; Rydin, 2000), I expect civic engagement to contribute to adaptive capacity because it reflects a community's ability to undertake collective actions.

Hypothesis 2.2: States with higher levels of civic engagement are more likely to engage in adaptation planning.

3.2.3 Political Interests

The impact of political interests on policy changes is unequivocal. Here I consider political factors from two perspectives: political ideology and competing priorities on the agenda. First, recent research on state-level energy policy innovations suggests political ideology, in terms of both citizen preferences and partisan legislative control, exerts a significant effect, and liberal states are generally more favorable to pro-environmental legislation (e.g., Chandler, 2009; Lyon and Yin, 2010; Huang et al., 2007; Carley and Miller, 2012). Given the current partisan divide over climate change, I expect political ideology to play a role in shaping state-level adaptation decisions.

Hypothesis 3.1: More liberal states, in terms of both elected officials and state legislature composition, are more likely to undertake adaptation planning.

Hypothesis 3.2: States with stronger environmental preferences are more likely to undertake adaptation planning.

Because government usually faces multiple issues on its agenda, the political interest in climate change and adaptation must compete with other priorities such as economic development and job growth. Here I consider the unemployment rate as one competing factor that may hamper the incentive to address climate adaptation.

Hypothesis 3.3: States with higher unemployment rates are less likely to pursue adaptation planning.

3.2.4 Regional Diffusion

Recent developments of the policy diffusion literature provide an additional lens to examine and understand how state policies are influenced by other governments in an increasingly interconnected world. Following Berry and Berry (1990), more studies have incorporated both internal determinants and regional influence to account for policy innovations.[66] In this paper I consider the potential regional diffusion of adaptation planning for two reasons. First, the theory of institutional isomorphism suggests organizational imitation (also called "mimetic processes") can be driven by uncertainty (DiMaggio and Powell, 1983). This explanation is particularly relevant for adaptation decisions because the highly uncertain nature of climate change and climate variability may make states more inclined to draw on each other's actions. Second, diffusion of adaptation decisions is more likely to occur within the same geographic region, because these states may share similar climatic characteristics and risks, which makes one jurisdiction's adaptation policy more relevant for the others.[67] Therefore, I expect geographic proximity to be an important mediating factor in the state-level diffusion of adaptation planning.

[66] However, many empirical studies on policy diffusion have been criticized for their simple focus on geographic clustering and ignorance of the causal mechanism of policy diffusion (Shipan and Volden, 2012; Karch, 2007). This literature has by far offered mixed evidence on policy diffusion because the empirical results are often sensitive to the choice of model specifications (Buckley et al., 2004).

[67] Karch (2007) summarizes that policy diffusion can arise from three processes: (1) imitation based on similar policy-relevant characteristics; (2) emulation during which policy makers learn from the successes and failures of others; and (3) competition with other jurisdictions. The diffusion of adaptation planning, if there is any, is more likely to fall into the first category, because most of these plans were made just recently and have not yet exhibited their effects, and also one's adaptation plan should not directly affect the interests of other states.

Hypothesis 4.1: States with more regional peers that have started adaptation planning are more likely to adopt adaptation plans.

Finally, it is noteworthy that the four sets of proposed explanatory factors are not mutually exclusive but rather may overlap each other. One single variable could fall into multiple categories of explanation and pick up different influences. As discussed earlier, the poor infrastructure not only reflects the societal vulnerability to climate impacts but also relates to the inadequate capacity to engage in adaptation and climate-proofing development. Additionally, the high unemployment rate could act as a political obstacle to the development of adaptation policy and also imposes resource constraints on undertaking adaptation activities.

4. Empirical Analysis

4.1 Data Description

My analysis uses data from a variety of sources to operationalize the four categories of factors that influence the development of state adaptation plans. First, I measure the recent climate impacts using fatalities and economic damages from extreme weather events including droughts, heat waves, floods, wildfires, severe storms, hurricanes and coastal hazards (including storm surges, coastal flooding and erosion), using data from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). I normalize the monetary damages that consist of both property and crop losses using its share of the affected state's GDP.[68]

[68] I choose to normalize disaster damage using its ratio of state GDP because the influence of economic losses on risk perception may likely depend on the economy size of the affected communities. However, I use the absolute level of fatalities as another impact measure because its effect on perceived risks would be less subject to a state's aggregate characteristics such as population size. In particular, all these events are natural disasters and the human losses they caused are found to have little correlation with a state's total population.

To measure a state's aging population, I use the 2010 Decennial census data to calculate the percentage of population at the age of 65 and above. I measure the size of a state's agriculture sector by dividing its annual agricultural production by its total GDP, using the data from the Bureau of Economic Analysis. I obtain the information on the length of states' ocean coastlines from the National Oceanic Atmospheric Administration (NOAA). I measure a state's coastal economy size using the percentage of its GDP contributed by its coastal shore adjacent counties, using the data compiled by the National Ocean Economics Program from the reports by the Bureau of Labor Statistics for the coastal counties. To measure a state's forest cover, I use the data from the United States Department of Agriculture Economic Research Service. I measure a state's infrastructure using the data on road bridges from the Department of Transportation.[69]

For the adaptive capacity variables, I measure a state's income level using data on median household income from the Bureau of Economic Analysis.[70] To measure state-level civic engagement, I use a variable from the 2008-2010 Civic Health Assessment Civic Engagement data that estimates the proportion of population who often attend public meetings. This data set is compiled and collected by the National Conference on Citizenship through the Current Population Survey (CPS) Supplements on Voting, Volunteering and Civic Engagement.

For the political interest variables, I use the data on party affiliation of state governors and partisan legislative control from the Council of State Governments. To capture states' environmental preferences, I follow previous studies (e.g., Lyon and Yin, 2010) and use the average League of Conservation Voters (LCV) scores of Senators and Representatives in each state. The LCV scores reflect the voting records of all members of Congress on selected key

[69] I use the percentage of road bridges that are categorized as either "structurally deficient" or "functionally obsolete" as a proxy for poor infrastructure.

[70] There are multiple measures of state income I can potentially use in this analysis. I have considered using GDP per capita but found it is highly correlated with the coastal economy variable.

environmental issues, with a range from 0 to 100 (a higher value indicates more votes in favor of environmental legislation). My data on the state-level unemployment rate are from the U.S. Department of Labor Local Area Unemployment Statistics.

Finally, the regional diffusion variable measures the percentage of states within the same climate regions that have started adaptation planning other than the state of interest, lagged by one year. Appendix 2 presents my regional division criteria, which is based on the 2014 National Climate Assessment. All the variables discussed above are summarized in Table 3-1, including their data sources. Table 3-2 presents the descriptive statistics.

4.2 Model Specification

To empirically examine the factors that influence the development of state adaptation plans, I follow the standard approach in the policy innovation literature by using a discrete-time EHA (Berry and Berry, 2007). This approach treats time as discrete units (taking positive integer values $t = 1, 2, 3\ldots$), and includes a total of n independent individuals (i=1, 2, 3…n) observed from at a certain starting point t_1 through t_i, at which point either an event occurs or the observation is censored (Allison, 1982).[71] The discrete-time survival analysis is used to model the hazard rate, which is the conditional probability that an individual will experience the event during a particular time period, given that it has not experienced it before.

Specifically, I estimate the hazard rate P_{it} (for a state i in the year t) using a logistic model that incorporates a vector of both time varying and time-invariant covariates X, their corresponding

[71] Right censoring is a common problem in longitudinal data, which occurs when some individuals do not experience any events so an event time cannot be measured. An important advantage of survival analysis is its capacity to handle the right censoring problem (Allison, 1982).

parameters β, the constant α, and baseline hazard rate, a(t), which is a function of survival time t. I cluster standard errors at the state level to account for the potential heteoroskedasticity.

$$(1) \qquad \text{logit}(P_{it}) = \log \frac{P_{it}}{1-P_{it}} = \alpha + \beta X + a(t);$$

Using the survival model to predict the probability of policy adoption raises several empirical issues that require careful attention. First, modeling the timing of a policy change is complicated by the fact that the development of an adaptation plan usually takes multiple years. Figure 2 shows the timeline and duration of states' planning process. Here I consider the onset (starting year) of the entire planning process as the event to be explained, because of my focus on the drivers of adaptation planning. Thus, to be more specific, the conceptual dependent variable P_{it} is the conditional probability that a state i began to prepare for its adaptation plan in year t.[72] Because the event is now defined as the onset of planning, states with plans in progress are also considered as "adapting" states, while states that have not yet started adaptation planning are treated as right censored.

Second, a starting year has to be chosen, which implies that all states have been "at risk" of starting adaptation planning since then (Box-Steffensmeier and Jones, 1997). As Figure 2 shows, adaptation planning started in seven states (AK, FL, MD, NH, VA, WA, WI) as early as 2007. But studies suggest that public concerns over climate change had been arising prior to that (e.g., Brulle et al., 2012).[73] I deliberately choose 2005 as the starting year of my sample, considering two

[72] The observed dependent variable is a binary variable that equals 1 when a state i began the planning process in year t and zero otherwise.
[73] Brulle et al. (2012) used the data from 74 separate surveys from 2002 to 2010 to develop a national aggregate index of public opinion on climate change, which started to increase around 2004 and peaked in 2007, which appears to be consistent with the wave of adaptation planning we have observed in this study.

important events that occurred in this year that may make all states "at risk" of adaptation planning. The first one is marked by the climate change conference held in King County, Washington, which engaged a broad range of stakeholders, state and local government officials to discuss their climate adaptation strategy. The second is Hurricane Katrina, which prompted considerable discussion on climate change.

Third, the functional form of a(t) needs to be specified, which allows the baseline hazard rate to change over time.[74] In this paper I allow for duration dependence considering the potential effect of the accumulation of information on climate change (e.g., observational data, climate science) on adaptation decisions. Because such information generally increases with time but is hard to quantify as a specific variable, including duration variables can help account for the information effect. I specify a(t) using a quadratic function of survival time t.[75]

My study sample includes 50 U.S. states over the period 2005-2013, for which I assemble a pooled cross-sectional time-series data set with state-year being my unit of observation. As a standard data-construction approach in EHA, I remove all observations for a given state for years once it starts the planning process because it already falls out the risk set of experiencing the event.

4.3 Empirical Findings

4.3.1 Baseline model

[74] The recent literature on policy innovation using EHA views the inclusion of a(t), also known as duration dependence, as an issue entailing both substantive and statistic importance (Buckley and Westerland, 2004).

[75] As noted in Buckley and Westerland (2004), there are different approaches to modeling duration dependence, such as including discrete-time dummy variables (non-parametric approach) or time/time-transformed variables (a parametric approach that imposes assumptions on the functional form of the time effect). Here I did not take the non-parametric approach for the sake of model parsimony. To find the proper duration variables, I conducted a set of tests using a simple time counter, quadratic and cubic terms of time trend as well as natural log of time. I choose the quadratic specification based on the likelihood ratio test and Akaike information criterion.

As laid out in Section 3, my empirical analysis considers the impacts on state-level adaptation planning of various state characteristics that reflect their climate risks, adaptive capacity, political interests and influences from nearby adapting states. Table 3-3 presents the regression results for equation (1) where a state's recent climate experiences are measured by the total economic or human losses caused by major weather/climate hazards (including heat waves, droughts, flooding, severe storms, hurricanes, coastal events and wildfires) in the past two years. I choose to focus on the past two years based on a set of sensitivity tests, which show that disaster losses generally become insignificant beyond year *t*-2.[76] Columns 1 and 2 report the logit coefficient estimates and average marginal effects, respectively, when disaster impact is measured by monetary damages, while columns 3 and 4 report the same estimates when impact is measured by fatalities.

First of all, I find that a state's likelihood of undertaking adaptation planning increases significantly with the severity of climate-induced disasters it has experienced recently. Specifically, as a state's total climate-related damages that occurred in the past two years increase by one percent as a fraction of its GDP, the state's probability of undertaking adaptation planning will increase by 0.4 percent on average. To put the coefficient into context, the 2013 Colorado floods, which caused over one-billion-dollar in damages that would account for about 6 percent of a median state GDP, would increase its likelihood of adaptation planning by 2.4 percent. As for climate-related fatalities, an additional 100 deaths would increase a state's likelihood of adaptation planning by 3 percent on average. To put this coefficient into perspective, Hurricane Sandy, which caused around 285 deaths, would increase the likelihood of undertaking adaptation planning by 9 percent.

As another aspect of climate risks, the vulnerability variables produce mixed evidence on their effects on the state-level adaptation decisions. For coastal characteristics, I find that states with

[76] Appendix 3 provides full results of the sensitivity analysis.

longer ocean coastlines and larger coastal economies are more likely to pursue adaptation planning. Specifically, the probability of making adaptation plans would increase by roughly 3 percent on average if a state's ocean coastline length increases by one thousand miles, or if the ratio of its coastal economy increases by one standard deviation. A state's forest coverage also has a significant and positive effect on its probability of developing adaptation plans, which is consistent with my hypothesis. Although these results suggest that climate vulnerability may serve as a motivation for adaptation, the other variables provide less clear support. The estimated effect of the elderly variable is negative and statistically insignificant. But this finding is not surprising because the elderly may perceive climate change as a problem less likely happen or intensify during their lifetimes, so that they show less support of adaptation planning.

The estimated coefficient on the agriculture variable is positive but statistically insignificant, which indicates no clear relationship between a state's agricultural economy and its decision on adaptation planning. One possible explanation is that the heavy agricultural subsidy provided by the federal government may distort states' incentive to adapt agriculture to climate change, which suggests a moral hazard problem. Another reason may be the major agricultural states in the U.S. are also more politically conservative and therefore, the agricultural variable does not provide additional explanatory power after controlling for a state's political ideology.

The estimated coefficient on the poor infrastructure variable is negative and significant, which implies that states with more infrastructure at risk are less likely to undertake adaptation planning. This result may suggest that not all aspects of vulnerability would necessarily translate to the motivation to reduce vulnerability to climate change. In fact, vulnerability may relate to the inherent unwillingness or inadequate capacity to address climate change, which may limit further actions on climate adaptation.

Table 3-3 also shows that both income and civic engagement have a positive and significant impact on a state's decision to plan for adaptation, which provides support for the adaptive capacity hypothesis. Specifically, I find that the likelihood of states' undertaking adaptation planning would increase by 4 percent when median household income increases by ten thousand dollars, all else equal. The result for the public meeting attendance variable suggests that civic engagement plays an important role in facilitating collective actions in the area of adaptation planning.

With respect to political ideology, the only variable that emerges as statistically significant is the state-level environmental preference with the coefficient in the expected direction. The probability of a state's developing an adaptation plan would increase by 5.5 percent with one standard deviation (27.61) increase in its LCV score. Neither of the partisan variables has an estimated coefficient that is significantly distinguishable from zero, after controlling for a state's general environmental preference. The estimated effect of unemployment rate also insignificant, which provides unclear evidence on the competing effect of other pressing issues, particularly job growth, on the state-level adaptation decision.

My results do not provide clear support to the hypothesis of regional diffusion of adaptation planning, since the variable that tracks nearby state's adaptation status is statistically insignificant. This may be because the diffusion variable is highly correlated with the quadratic time trend.[77] It should also be acknowledged that grouping states by climatic regions may assign some neighboring states to different regions and thus fail to account for diffusion among them. To address this issue, I took another approach by creating bilateral spatial weights and including all states in calculating a weighted sum of external influence, following Aichele and Felbermayr (2012). Specifically, this spatial diffusion variable is computed as $\sum_{j \neq i}(POP_{j,t}\, / Dist_{i,j})PLAN_{j.t}$,

[77] I find that the diffusion variable is positive and statistically significant if I drop the baseline hazard rate or only include the time trend. This suggests the possible multicollinearity between the diffusion variable and my duration variables.

where $Dist_{i,j}$ is geographic distance between states i and j, and $POP_{j,t}$ is population of state j. $PLAN_{j.t}$ is a binary variable taking the value 1 if state j starts adaptation planning in year t. By creating the bilateral spatial weights, I allow the influence of other adapting states to diminish with the distance from state i and also to increase with their population size. Data on population and inter-state spatial distance matrices are separately drawn from the Bureau of Economic Analysis and Scott (2005). In Table 3-4 I present the estimation results using the alternative spatial diffusion variable, lagged by one year. Similarly, column 1 and 3 report the logit coefficients, and column 2 and 4 report the estimates of average marginal effects. The new results might be suggestive of some spatial diffusion of state-level adaptation initiatives, since the estimated coefficients are marginally significant in both cases (using either dollar damages or deaths to measure recent disaster severity). But the evidence is far from conclusive and should be interpreted with caution. In the meantime, employing the new diffusion variable does not alter the main estimation results for other explanatory variables, except that the social capital variable becomes insignificant in column 1.

One thing important to note here is that policy diffusion/imitation might occur through multiple channels and in different contexts, and it is highly possible that geographic proximity is not the only mediating factor. Other factors such as ideological similarities might also play an important role when states exert influence on each other's decision of adopting climate policies. I leave investigating this issue for future research.

Finally, to provide some perspective on the predictive power of my empirical model, I present a classification table (Table 3-5) listing states that are either correctly or falsely predicted on their adaptation status, using the estimated coefficients in column 1 of Table 3-3 and a 50% cutoff point for predicting success. The table has four cells indicating (A) states that are correctly predicted to have adaptation plans; (B) states that have plans but are predicted not; (C) states that have no plans but are predicted to have plans; and (D) states that are correctly predicted to have no plans. The table shows that my model has correctly predicted 10 out of the 22 states that have actually initiated adaptation planning. Notably, my model predicts that five states (listed in Cell C) would start planning earlier than they actually did. Another 12 states (listed in Cell B) are predicted to have no plans in the years when they actually started adaptation planning. The model appears to have correctly predicted all the states that have never initiated adaptation planning.

4.3.2 Disaggregating climate hazards

Although using the total climate-induced damages captures a state's aggregate climate risk level, it is important to note that different types of climate hazard usually generate different levels of consequence and may have different implications for adaptation responses. As my descriptive statistics indicate (Table 3-2), states' total climate-related losses are highly dominated by damages caused by hurricanes. This is consistent with the statistics from the National Climatic Data Center on the distribution of damages from U.S. billion-dollar climate disaster events.[78] More specifically, their statistics indicate that over the 1980-2013 period, hurricanes not only caused the most damage but also the highest average cost per event. In addition to the variation in damage scale, climate impacts could also be different depending on the sectors affected and how losses are measured. For example, droughts usually affect the agriculture sector the most and can cause significant crop losses, but they rarely cause direct human losses. To the contrary, heat waves pose a serious threat to public health by causing heat-related deaths and illness, while the direct economic losses from heat wave are negligible compared to those caused by other hazards. Finally, disasters differ in

[78] http://www.ncdc.noaa.gov/billions/, accessed on September 1, 2012.

their impact timeframes. Some hazards, such as hurricanes and heat waves, have a sudden onset and only last for a relatively short time period. Chronic hazards, such as drought and sea level rise, have a much less noticeable onset and their consequences do not manifest until they have accumulated for a long time period. This distinction can also affect the perception of climate change and how quickly people respond to these events.

To further assess the effect of different climate hazards on adaptation planning, I disaggregate the total impacts by the types of climate hazard and compute the sum of hazard-specific damages over different time periods.[79] Specifically, I create three disaster groups: (1) hurricanes and other coastal hazards; (2) heat waves, droughts and wildfires (all related to hot and dry weather); and (3) flooding and severe storms.

As shown in Table 3-6, Panel A, monetary losses caused by coastal hazards in the past two years have a significant and positive effect on a state's probability of pursuing adaptation planning, though this variable becomes insignificant beyond the two-year lag. This is consistent with my finding in Table 3-2, because hurricanes have accounted for most of the climate-related damages (as indicated in the descriptive statistics). Cumulative losses from hot and dry weather hazards (as dominated by drought damages) have a consistently positive impact across different time horizons. This result may be attributed to the chronic nature of drought events. Because the drought impact is usually manifested after it persists for a certain period of time, droughts may cause a relatively longer lag in adaptation responses.

Panel B reports the estimated coefficients for hazard-specific fatalities. Again, the impact of coastal disasters on adaptation planning is mostly concentrated in the most recent two years. Only

[79] Ideally, the analysis would still include hazard-specific damages in distributed lag structure. But this approach would ask too much from the data, especially given my relative small sample size. Using the sum of hazard-specific damages over multiple years is more parsimonious. It also allows me to identify the impacts of different hazards in different time scales. The downside is to assign the same weight to different years. But this problem could be alleviated because my analysis uses different time scales.

fatalities for the second disaster category (as largely dominated by heat waves) in the past two years have a significant and positive impact, also suggesting a short-term response.[80] Finally, results in both Panel A and B show that recent flooding and storm events are not an important predictor of states' planning decisions. This might be because the link between these events and climate change is less clear, at least from the public perception perspective.

Overall, these results suggest that different types of climate hazards may exert different influences on prompting subnational adaptation responses. One thing to note here is that the coefficients for hot and dry weather hazards are much larger for those of coastal hazards (e.g., hurricanes). This is potentially because hurricanes are typically more destructive and result in much larger losses than other extreme weather events. In a scenario where drought, heatwaves, and wildfires cause the same amount of damage as hurricanes, the former might be perceived to be more severe and salient, and therefore have a larger impact on adaptation decisions.

5 Discussion and Conclusion

Over the past decade, formal planning for climate change adaptation has emerged rapidly at all levels of government in the United States. Planning has been a traditional approach to preparing for natural hazards and extreme events in this country, and is found to have effectively reduced disaster losses (Burby, 2005). Adaptation planning is related to but distinct from hazard mitigation planning. Given the uncertain, complex and wide-ranging impact of climate change, adaptation planning requires forward thinking, scientific analyses and an integrated approach. It is a new task for government, which marks the beginning of planned adaptation activities undertaken by government on behalf of society.

[80] Drought is excluded because no direct deaths are reported.

This paper draws upon the policy innovation literature and employs an EHA to explain the state-level decision to develop comprehensive climate adaptation plans. Overall, I find that states' adaptation decision is driven by a combination of internal factors related to its climate risks, adaptive capacity, and environmental preferences. There is no strong evidence suggesting regional diffusion of adaptation planning among states.

My results highlight several important implications for subnational adaptation actions. First, the finding that recent extreme weather events would accelerate a state's adaptation planning efforts confirms the prevailing view that most adaptation actions are reactive to problems after they are manifested (e.g., Bierbaum et al., 2013). It further suggests that the federal government has an important role to play in encouraging and informing proactive subnational adaptation before an event occurs. This finding also provides implications on the framing of climate change, in particular on how to leverage these extreme events to create the political window for promoting climate adaptation on the political agenda.

Second, I find that a state's tendency to engage in adaptation planning is affected by its vulnerability to climate change and adaptive capacity. While some characteristics that may aggravate a state's exposure and sensitivity to climate impacts (e.g., ocean coastlines, size of coastal economy, forest cover) can move the state toward adaptation planning, some aspect of vulnerability (e.g., weak infrastructure) is found to have a negative effect on state-level adaptation decision. This finding implies that communities that are socially vulnerable to climate change may also lack adequate capacity or resources to adapt. Along with my other finding on the positive correlation between state affluence and its probability of undertaking adaptation planning, these results highlight the implications of economic inequality for adaptation actions. To address this problem requires more coordinated efforts, at both the federal and state level, integrating climate adaptation and economic development. For example, the federal government may provide financial incentives and support to encourage climate-proof development, particularly on investment in long-term capital stocks such as infrastructure.

Third, in this paper I consider state-level adaptation planning as not just a policy innovation but also a collective decision to address climate change. My findings suggest that both civic engagement and environmental preferences play an important role in facilitating adaptation planning, which enriches our understanding of climate adaptation as a collective action and social aspects of adaptive capacity. It may also provide policy makers with additional insights that may help facilitate the planning process.

Finally, assessing statewide adaptation plans provides the very first step to understanding subnational adaptation decisions. Although an adaptation plan is an important prediction for coordinated actions, it is also true that plans do not necessarily guarantee concrete adaptation actions. How these plans are actually used to guide adaptation actions and their effect in reducing the negative climate impacts deserves more attention and investigation in future research. To be able to track and evaluate the adaptation progress also requires more updated information provided by state governments in a regular and timely manner. Moreover, it is reasonable to expect that these adaptation plans would also evolve with changes in economic situations and political leadership, as well as with more feedback from the ongoing adaptation activities. Therefore, it would be also interesting to further explore adaptation planning as a recurrent and ongoing process. Examining the evolution of adaptation plans will provide additional insights to understand the determinants of adaptation policy development, and also shed light on the implication of political changes on states' persistent efforts to address climate adaptation. Last but not least, to fully understand the dynamics of subnational adaptation actions requires more attention given to local governments. In fact, some cities have already adopted local adaptation plans even though their state governments have not yet taken any formal actions. The interactions between state and local governments in adaptation planning and the potential vertical diffusion of adaptation strategies will be interesting issues for future research.

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Table 3-1 Variable and Data Description

Factors	Variable Measurement	Data Sources
Climate risks		
Impact of Extreme Weather Events	Fatalities and monetary loss (property and crop) from climate-related disasters (including floods, heat waves, droughts, wildfires, coastal disasters).	Spatial Hazard Events and Losses Database for the United States
Vulnerability	People at the age of 65 and above as % of a state's total population*	US Census
	Agricultural production as % of state total GDP	Bureau of Economic Analysis
	Length of ocean coastline in thousand miles*	NOAA
	Coastal economy as % of state total GDP	National Ocean Economics Program, Bureau of Labor Statistics
	Forest land as % of state total land area*	Department of Agriculture
	Poor road bridges as % of state total road bridges	Department of Transportation
Adaptive Capacity		
Income	Median household income (1000 dollars, adjusted at 2005 price) #	Bureau of Economic Analysis
Civic Engagement	Public meeting attendance (% of adults who say they often attend public meeting)*	National Conference on Citizenship, Current Population Survey
Political Interests		
Ideology	Party affiliation of state governor (=1 for democratic state governor)	Council of State Government
	Partisan Dominance in state legislature (= 1 if state Senate and House are both controlled by democratic party and 0 otherwise)	Council of State Government
Environmental preference	Average League and Conservation Voters scores of Senators and Representatives	League of Conservation Voters
Competing issues	Unemployment rate #	Department of Labor
Diffusion		
Spatial Diffusion	Percentage of other states within the same climate regions that have started adaptation planning #	Center for Climate and Energy Solutions; Georgetown Climate Center; EPA; my own online searches and e-mail inquiries.

Note: *indicates the independent variables are time-invariant. Specifically, the elderly variable is based on the 2010 census data. The forest land ratio is based on the 2007 data. The coastline describes the general outline of the seacoast, including large sounds and bays, with the data based on the 1948 measurement. The variables marked with "#" are included in the regressions with one year lag. For variables with "+", I consider their cumulative effects in a recent period by using either a distributed lags or sums over multiple years.

Table 3-2 Summary Statistics for Explanatory Variables

Variables	Mean	Std. Dev	Min	Max
The elderly (%)	13.28	1.51	7.7	17.3
Agricultural sector (%)	1.53	1.75	0.05	7.15
Coastline length (thousand miles)	0.14	0.64	0	6.64
Coastal economy (%)	17.86	30.14	0	100
Forest cover (%)	35.80	22.14	1.58	87.86
Poor infrastructure (%)	25.23	8.81	10.04	55.14
Median household income in year t-1 (thousand dollars adjusted at 2005 price)	52.23	7.92	36.64	77.51
Public meeting attendance (%)	10.86	3.36	6	21
Democratic governor	0.45	0.5	0	1
Democratic legislative control	0.39	0.49	0	1
League of Conservation Voter (LCV) score	44.68	27.61	0	100
Unemployment rate in year t-1 (%)	5.89	2.2	2.5	13.7
Percent nearby adapting states in year t-1	14	21	0	100
Total monetary losses as fraction of state GDP in the past two years (%)	0.51	3.21	0	32.40
Droughts	0.018	0.12	0	1.77
Heat waves	0.0003	0.002	0	0.027
Wildfire	0.005	0.05	0	0.8
Floods	0.1	0.49	0	6.19
Severe Storms	0.0005	0.003	0	0.03
Hurricanes	0.39	3.18	0	32.3
Coastal hazards	0.002	0.02	0	0.29
Total deaths in the past two years (persons)	14.37	54.83	0	690
Heat waves	4.22	10.74	0	71
Wildfire	0.3	1.82	0	22
Floods	3.2	6.02	0	53
Severe storms	0.11	0.47	0	4
Hurricanes	5.32	53.14	0	686
Coastal hazards	1.22	3.99	0	49

Table 3-3 Logistic Model of the Adoption of State-level Adaptation Planning

	With damages		With deaths	
	(1)	(2)	(3)	(4)
Total damages as fraction of GDP (%)	0.132**	0.42%		
	(0.0567)			
Total deaths (hundred)			0.804**	3%
			(0.329)	
The elderly (%)	-0.124	-0.4%	-0.0759	-0.2%
	(0.582)		(0.567)	
Agricultural sector (%)	0.106	0.3%	0.137	0.4%
	(0.401)		(0.381)	
Coastline length (thousand miles)	1.019***	3.3%	1.060***	3.4%
	(0.384)		(0.395)	
Coastal economy (%)	0.0264***	0.1%	0.0263**	0.1%
	(0.0101)		(0.0104)	
Forest cover (%)	0.0939***	0.3%	0.0960***	0.3%
	(0.0252)		(0.0263)	
Poor infrastructure (%)	-0.104*	-0.3%	-0.108*	-0.3%
	(0.0543)		(0.0562)	
Median household income in year t-1	0.112**	0.4%	0.122**	0.4%
(thousand dollars)	(0.0509)		(0.0530)	
Public meeting attendance (%)	0.175*	0.5%	0.187*	0.6%
	(0.104)		(0.103)	
Democratic governor	1.055	3.4%	1.101	3.5%
	(1.025)		(1.009)	
Democratic legislative control	-0.357	-1.5%	-0.379	-1.2%
	(1.030)		(1.043)	
League of Conservation Voter score	0.0486**	0.2%	0.0472**	0.2%
	(0.0239)		(0.0239)	
Unemployment rate in year t-1 (%)	-0.0636	-0.2%	-0.0589	-0.2%
	(0.183)		(0.184)	
Percent adapting states in year t-1 (%)	0.011	0.04%	0.0121	0.04%
	(0.0156)		(0.0155)	
t	4.487***	14.5%	4.570***	14.8%
	(1.192)		(1.214)	
t^2	-0.381***	-1.2%	-0.387***	-1.2%
	(0.119)		(0.121)	
Constant	-26.37***		-28.00***	
	(7.387)		(7.544)	
Observations	349		349	
AIC	111.2		110.7	
Log likelihood	-38.59		-38.37	

Note: Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
The damage variable is a state's total climate-related damages in the past two years (from droughts, heat waves, wildfires, hurricanes, flooding, severe storms, and other coastal hazards) as fraction of the state's GDP. The death variables measures the number of fatalities (in hundred) caused by climate hazards in the past two years. Column 1 and 3 report the logit coefficient estimates, and column 3 and 4 report the corresponding average marginal effect.

Table 3-4 Using alternative spatial diffusion measure

	With damages		With deaths	
	(1)	(2)	(3)	(4)
Total damages as fraction of GDP (%)	0.155**	0.49%		
	(0.0628)			
Total deaths (hundred)			0.945***	3%
			(0.363)	
The elderly (%)	-0.193	-0.6%	-0.141	-0.4%
	(0.663)		(0.650)	
Agricultural sector (%)	0.304	0.9%	0.357	1.1%
	(0.449)		(0.437)	
Coastline length (thousand miles)	0.119***	3.8%	0.126***	4.0%
	(0.0391)		(0.0409)	
Coastal economy (%)	0.0258**	0.8%	0.0257**	0.08%
	(0.0110)		(0.0113)	
Forest cover (%)	0.104***	0.3%	0.107***	0.3%
	(0.0302)		(0.0321)	
Poor infrastructure (%)	-0.109*	-0.3%	-0.113*	-0.4%
	(0.0614)		(0.0641)	
Median household income in year t-1	0.121**	0.4%	0.133**	0.4%
(thousand dollars)	(0.0532)		(0.0557)	
Public meeting attendance (%)	0.153	0.5%	0.165*	0.5%
	(0.0985)		(0.0988)	
Democratic governor	1.159	3.7%	1.228	3.9%
	(1.122)		(1.116)	
Democratic legislative control	-0.532	-1.7%	-0.565	-1.8%
	(0.982)		(1.004)	
League of Conservation Voter score	0.0581**	0.2%	0.0573**	0.2%
	(0.0277)		(0.0283)	
Unemployment rate in year t-1 (%)	-0.170	-0.5%	-0.170	-0.5%
	(0.187)		(0.188)	
Spatial diffusion in year t-1	0.00948	0.03%	0.0102*	0.03%
	(0.00590)		(0.00593)	
t	4.204***	13.5%	4.300***	13.7%
	(1.022)		(1.035)	
t^2	-0.360***	-1.2%	-0.367***	-1.2%
	(0.108)		(0.110)	
Constant	-25.94***		-27.93***	
	(7.577)		(7.654)	
Observations	349		349	
AIC	109.821		109.23	
Log likelihood	-37.91		- 37.62	

Note: Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.
The damage variable is a state's total climate-related damages in the past two years (from droughts, heat waves, wildfires, hurricanes, flooding, severe storms, and other coastal hazards) as fraction of the state's GDP. The death variables measures the number of fatalities (in hundred) caused by climate hazards in the past two years. Column 1 and 3 report the logit coefficient estimates, and column 3 and 4 report the corresponding average marginal effect.

Table 3-5 Logit Classification Table

Classified	Having plans	Having no plans	Total
Predicted to have plans	**A** Alaska 2007 Connecticut 2008 Delaware 2009 Hawaii 2011 Maine 2007 Maryland 2009 New Hampshire 2007 New York 2009 Oregon 2009 Vermont 2008	**C** Delaware 2008 Hawaii 2009 Maryland 2008 New Jersey 2009 Oregon 2008	15
Predicted to have no plans	**B** California 2008 Colorado 2008 Florida 2007 Massachusetts 2008 Minnesota 2009 New Jersey 2011 North Carolina 2009 Pennsylvania 2010 Rhode Island 2010 Virginia 2007 Washington 2007 Wisconsin 2007	**D** *All others*	334
Total	22	327	349

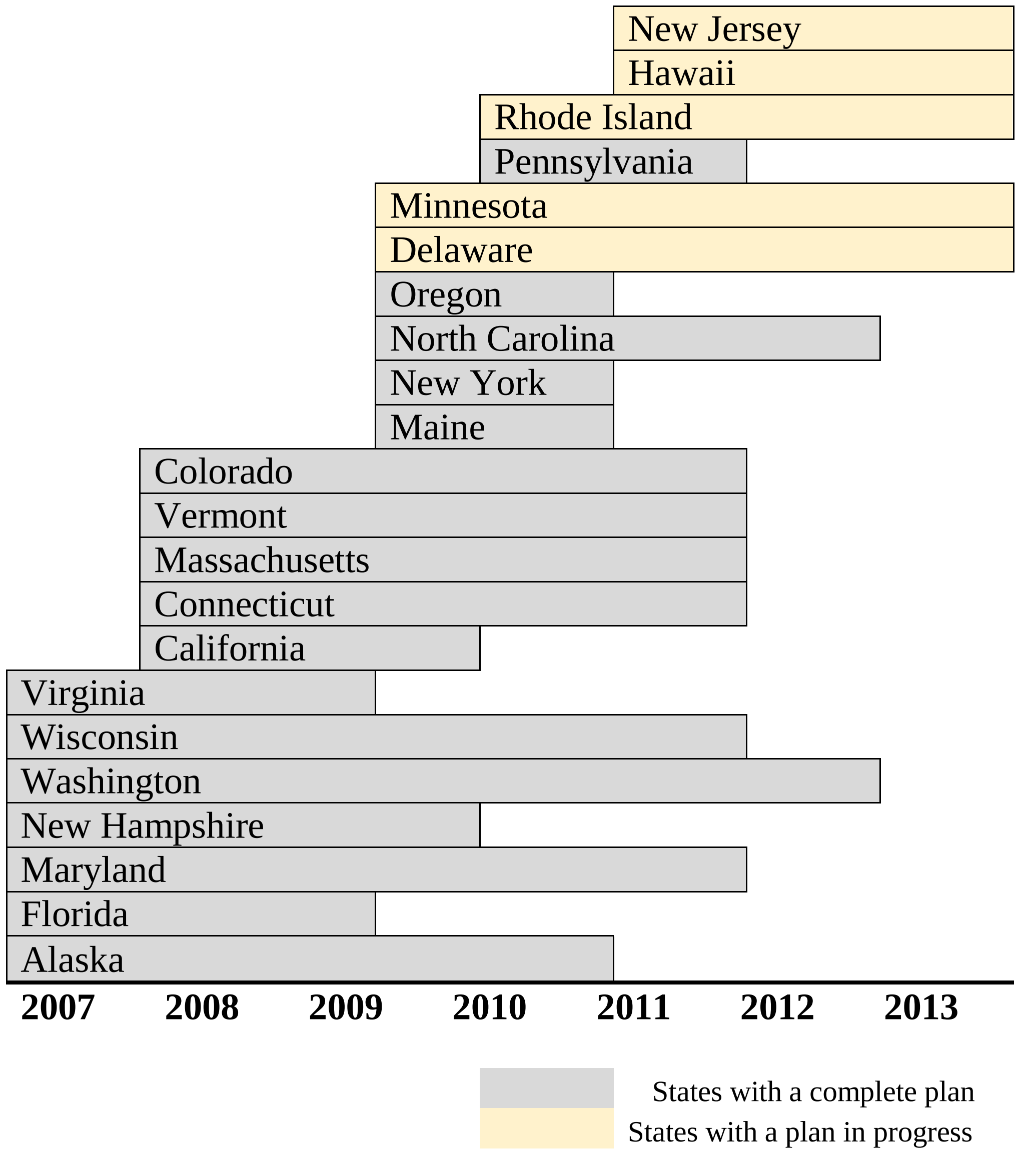
Table 3-6 Logistic model of adaptation planning (hazard-specific impacts)

	Past two years	Past three years	Past four years
Panel A – Impact measured by damage as fraction of GDP (%)			
Coastal hazards	0.132**	0.0736	0.0307
	(0.0543)	(0.0562)	(0.0582)
A.M.E	0.4%	0.2%	0.1%
Drought, wildfires, Heat waves	3.347*	3.361*	3.487**
	(1.831)	(1.844)	(1.765)
A.M.E	10.8%	10.8%	11.3%
Flooding and severe storms	-2.489	-0.198	-1.620
	(7.876)	(0.628)	(3.772)
A.M.E	-8%	0.6%	-5.2%
Panel B – Impact measured by number of deaths (persons)			
	Past two years	*Past three years*	*Past four years*
Coastal hazards	0.00793***	0.00513*	0.00373
	(0.00251)	(0.00275)	(0.00312)
A.M.E	0.02%	0.016%	0.01%
Heat waves and wildfires	0.0441*	0.0531	0.0303
	(0.0242)	(0.0390)	(0.0307)
A.M.E	0.13%	0.16%	0.1%
Flooding and severe storms	-0.384	-0.212	-0.0456
	(0.266)	(0.211)	(0.128)
A.M.E	-1.1%	0.6%	-0.14%

Note: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
A.M.E represent the average marginal effect of the logit coefficient estimates. Panel A reports the results when disaster damage is measured by cumulative economic losses (as fraction of state GDP) for the three hazard groups over the past 2-year, 3-year and 4-year period. Panel B reports the results using cumulative death tolls as a measure of disaster impact.

Figure 3-1 Progress on Adaptation Planning in the United States

Figure 3-2 Timeline: Development of Statewide Adaptation Plans



Note: For Washington and Maryland with multiple adaptation plans, the completion year denotes the year of publication of their last planning document.

Appendix

Appendix 1. Descriptive analysis of statewide adaptation plans.

The two primary databases I use to identify statewide comprehensive adaptation plans are from the Center for Climate and Energy Solutions (C2ES) and the Georgetown Climate Center.[81] The two databases are cross-referenced and therefore, highly similar.[82] I rely more heavily on the C2ES dataset because this is the source more commonly used in studies of domestic adaptation planning, including the 2014 National Climate Assessment. Furthermore, I also use the information compiled by the Environmental Protection Agency on statewide adaptation actions to check whether the data from the first two sources have included all states with extant planning documents. Based on these data sources, I also conduct online searches and make e-mail inquiries to state environmental agencies to construct my database of statewide adaptation planning documents.[83]

I undertake a systematic review of the identified state adaptation plans and summarize their planning documents in Table 3-A1a, including plan titles, preparation organizations, document lengths and publication years. For states with a complete plan, most of their planning documents have exclusively focused on climate change adaptation, while four states (Florida, New Hampshire, New York, and Virginia) have adaptation plans embedded in a broader climate change action plan, which also include planning components related to greenhouse gas mitigation.

Although these plans meet the basic criteria for analysis, the breadth and depth of the planning content vary considerably across states. Notably, some states have more than one adaptation plan.

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[81] The former database is accessed on http://www.c2es.org/us-states-regions/policy-maps/adaptation, while the link to the latter is http://www.georgetownclimate.org/adaptation/state-and-local-plans.

[82] Both two databases use comprehensiveness (i.e., covering multiple climate-sensitive sectors) as a key criteria to identify statewide climate adaptation plans. But one difference is that C2ES also include states if they have a collection of sector-level plans that collectively represent all major sectors.

[83] I have also included North Carolina as a "completion" state through communication with the officials from its state environmental agency. Their planning document is not mentioned by either C2ES or Georgetown Climate Center, but is included in the database of adaptation examples compiled by the EPA.

For example, Maryland conducted adaptation planning in two stages: the first one focusing specifically on coastal management and the second one dealing with multiple climate-relevant sectors. The state of Washington released its first adaptation plan in 2008, and drew on this initial effort to finalize its integrated climate adaptation strategy in 2012.

In terms of the origin, these state adaptation plans were developed through either a top-down request, in the form of executive orders issued by state governors or requirement from the state legislature, or a bottom-up initiative by state agencies. Table 3-A1b provides a brief description of how these plans were initiated in each state, including the five states with an adaptation plan-in-progress. The fact that a majority of the adaptation plans were guided by the governors' requirements may illustrate the importance of political entrepreneurs in shaping state-level climate policy agenda. Besides the elected leaders, the agency's bottom-up approach to adaptation planning reflects their rising power in the new era of governance, and in particular, their capacity of engaging stakeholders and coordinating partnerships.

Comprehensive adaptation planning requires consideration of the complex effects of climate change as well as their implications for various sectors. Table 3-A1c presents the common concerns in these plans, classified by either impacts or sectors. As Panel A shows, the climatic impacts most often discussed in these plans include not only the gradual changes (e.g., increased temperatures and sea level rise) but also extreme weather events (e.g., flooding, storm events, droughts, heat waves) that are expected to become more frequent and intense as a result of climate change. These plans also consider other secondary effects, particularly decreased air quality and ecological changes. In all the plans, the climate change-related impacts and corresponding adaptation strategies are explored in a multi-sector setting (as shown in Panel B), with most attention given to public health, agriculture, ecosystem, coastal management, water resource and infrastructure. For each sector, specific adaptation strategies are proposed in these plan documents. Additionally, most of the state plans have identified a set of overarching strategies to guide their general adaptation practices (as shown in Table 3-A1d), which include, for example, advancing climate research and promoting the public awareness on climate adaptation as well as incorporating climate adaptation into existing planning and programs (known as "mainstreaming").

It is important note that some traditional government functions may have already incorporated climate change into their planning processes without necessarily developing a so-called adaptation plan. To address this concern, I compared my list of "adapting" states with a recent study, which rates the discussion of climate change in statewide hazard mitigation plans (Babcock, 2013).[84] Table 3-A1e provides a comparison between the two lists of states. It indicates that most of the states that have already addressed adaptation in their existing framework of natural hazard mitigation are also more likely to develop an independent adaptation plan.

[84] The study conducted in the Columbia Law School provides a rating for each state to assess its planning component particularly related to climate change based on their state hazard mitigation planning documents. More specifically, its ranks states by four categories; a higher ranking indicates more substantial discussion of climate change and adaptation actions.

Table 3-A1a: Summary of Statewide Adaptation Plans

State	Planning document title	# of Pages (discussing adaptation)	Publication year	Preparing organization
Alaska	Alaska's Climate Change Strategy: addressing impacts in Alaska	94	2010	The Alaska Climate Change Adaptation Advisory Group (including four working groups)
California	2009 California Climate Adaptation Strategy	200	2009	The California Natural Resources Agency (in collaboration with other agencies)
Colorado	Colorado Climate Preparedness Project Final Report	114	2011	Western Water Assessment for the State of Colorado
Connecticut	Connecticut Climate Change Preparedness Plan	111	2011	Adaptation Subcommittee of the Governor’s Steering Committee on Climate Change
Florida	Florida's energy & climate change action plan	7/124	2008	Governor's Action Team on Energy and Climate Change
Maine	People and Nature Adapting to a changing climate: charting Maine's Course	12	2010	Maine Department of Environmental Protection
Maryland	Comprehensive Strategy for Reducing Maryland's Vulnerability to Climate Change phase 1: sea-level rise and coastal storms	44	2008	The Maryland Commission on Climate Change Adaptation and Response Working Groups.
Maryland	Comprehensives strategy for reducing Maryland's vulnerability to climate change. Phase ii: Building societal, economic, and ecological resilience	124	2011	The Maryland Commission on Climate Change Adaptation and Response Working Groups.
Massachusetts	Massachusetts Climate Change Adaptation Report	128	2011	Massachusetts Executive Office of Energy and Environmental Affairs and the Climate Change Adaptation Advisory Committee
New Hampshire	New Hampshire Climate Action Plan: A plan for New Hampshire's Energy, Environmental and Economic Development Future.	6/82	2009	New Hampshire Climate Change Policy Task Force; Department of Environmental Services
New York	New York State Climate Action Plan Interim Report	86/428	2010	New York State Climate Action Council; New York State Department of Environmental Conservation (DEC); New York State Energy Research and Development Authority (NYSERDA)
North Carolina	Climate Ready North Carolina: Building a resilient future.	152	2012	North Carolina Interagency Leadership Team (ILT)
Oregon	The Oregon Climate Change Adaptation Framework	151	2010	State of Oregon (state agencies) Oregon Climate Change Research Institute (OCCRI)
Pennsylvania	Pennsylvania Climate Adaptation Report	104	2011	Pennsylvania Department of Environmental Protection
Vermont	Vermont Adaptation White Papers	58	2011	Vermont Agency of Natural Resources
Virginia	Virginia's Final Report: A Climate Change Action Plan	7/125	2008	Virginia Governor's Commission on Climate Change
Washington	Leading the Way: Preparing for the Impacts of Climate Change in Washington	84	2008	Department of Ecology, Department of Community, Trade and Economic Development
Washington	Preparing for a Changing Climate: Washington State’s Integrated Climate Response Strategy	207	2012	Department of Ecology, Four advisory groups
Wisconsin	Wisconsin's Changing Climate: Impacts and Adaptation	226	2011	Wisconsin Initiative on Climate Change Impacts (WICCI) -- the Nelson Institute for Environmental Studies at the University of Wisconsin-Madison and the Wisconsin Department of Natural Resources.

Note: As discussed in the text, Maryland and Washington have released more than one statewide adaptation planning documents. Column 3 (# of pages) compares the length of various state adaptation plans. For those marked with “/”, this means their discussions of adaptation planning are incorporated in a broad state climate action plan (normally containing GHG mitigation strategies), with the number after “/” indicating the pages of the entire document.

Table 3-A1b Summary on the Initiation of Statewide Adaptation Plans

State	Year	Governor	Legislature	Agency	Note
States with a completed adaptation plan					
Alaska	2007	x			Governor Sarah Palin signed Administrative Order 238, which established and charged the Alaska Climate Change Sub-Cabinet to advise the Office of the Governor on the preparation and implementation of a comprehensive Alaska Climate Change Strategy (AO 238).
California	2008	x			Governor Schwarzeegger's Executive Order S-13-08 directed state agencies to plan for climate impacts and collaborating on a statewide climate adaptation strategy. The Natural Resource Agency is tasked with overseeing the development of the state adaptation plan
Colorado	2008	x			On April 22, 2008, Governor Ritter issued Executive Order B007 08 to create the state's Climate Change Advisory Panel and authorize the panel to make recommendations to achieve the goals of Colorado's Climate Action Plan, including mechanisms for adaptation planning.
Connecticut	2008		x		Public Act No. 08-98, An Act Concerning Connecticut Global Warming Solutions, Section 7 required the Governor‘s Steering Committee on Climate Change to establish an Adaptation Subcommittee to evaluate the projected impacts of climate change on Connecticut and develop strategies to mitigate these impacts.
Florida	2007	x			Executive Order (07-128) signed by Governor Charlie Crist created the Governor's Action Team on Energy and Climate Change and tasked it with creating a comprehensive Florida Energy and Climate Change Action Plan to achieve or surpass the statewide targets for greenhouse gas reduction.
Maine	2009		x		The state legislature passed a resolution ("Resolve, To Evaluate Climate Change Adaptation Options for the State": Maine SP0163 / LD 460) charging the Department of Environmental Protection to initiate a stakeholder-based process evaluating options and actions to prepare for the impacts of climate change.
Maryland	2007	x			Governor Martin O'Malley signed an Executive Order (01.01.2007.07) establishing the Maryland Climate Change Commission (MCCC) and charging them with developing a state climate action plan that addresses both mitigation and adaptation.
Massachusetts	2008		x		The Global Warming Solutions Act, passed by the Massachusetts Legislature and signed by Governor Deval Patrick, created the Climate Change Adaptation Advisory Committee which is responsible for analyzing strategies for adapting to predicted impacts of climate change in the Commonwealth.
New Hampshire	2007	x			Governor John Lynch issued EO 2007-3 creating the Climate Change Policy Task Force. The Task Force is comprised of 6 working groups, with one dedicated to Adaptation.
New York	2009	x			Executive Order 24 signed by Governor David Patterson created the New York Climate Action Council and charged it with creating a Climate Action Plan.
North Carolina	2009			x	Since 2009, the North Carolina Interagency Leadership Team (ILT) has been looking at how multiple government agencies could consider potential climate and extreme weather event impacts on their areas of responsibility. In March, 2010, the ILT hosted a workshop “Planning for North Carolina’s Future: Ask the Climate Question.”
Oregon	2009	x			In October 2009, Governor Ted Kulongoski asked the directors of several state agencies, universities, research institutions and extension services to develop a climate change adaptation plan.
Pennsylvania	2010			x	The Pennsylvania Climate Change Act, Act 70 of 2008 authorized the Department of Environmental Protection (DEP) to prepare a report recommending mitigation actions. Although not a requirement of Act 70, the DEP and the Climate Change Advisory Committee (CCAC) recognized the need to also address adaptation planning. During the 2009 meeting of the CAAC, a motion was

					made and passed with unanimous support that the action plans should include a recommendation to the Governor and the Pennsylvania General Assembly to address climate adaptation.
Vermont	2008	x			The Governor's Commission on Climate Change was created in 2005 by Governor James Douglas' Executive Order 07-05, tasked with developing a climate action plan on reducing GHG emissions. In 2008, a multi-agency Climate Change Transition Team was created to develop a work plan. The group released a draft work plan in 2008, which included an outline for the creation of a Climate Adaptation Plan.
Virginia	2007	x			Executive Order 59 (2007), signed by Governor Timothy Kaine in 2007, established the Governor's Commission on Climate Change that is responsible for creating a Climate Change Action Plan that would evaluate expected impacts of climate change and identify adaptation strategies.
Washington	2007	x			The state's 2008 adaptation plan was initiated by the Executive Order 07-02 issued by Governor Christine O. Gregoire, which requires identifying specific steps to prepare for the impact of global warming on multiple sectors.
	2009	x	x		The state's 2012 plan was guided by the requirement of state legislature and governor. The Washington State Legislature approved the State Agency Climate Leadership Act SB 5560, which included provisions in sections 10 through 13 for the formation of an "integrated climate change response strategy". Governor Gregoire's May 2009 Executive Order reinforced this requirement, directing the Department of Ecology to collaborate with affected local, state, and federal agencies to develop adaptation recommendations, guidelines, and tools.
Wisconsin	2007			x	In 2007, the Wisconsin Initiative on Climate Change Impacts (WICCI) was formed as a joint initiative between the Wisconsin Department of Natural Resources and the University of Wisconsin - Madison's Nelson Institute for Environmental Studies. WICCI is a unique and innovative process that relies on a bottom-up approach to engage scientists, researchers, and management agencies in understanding the impacts of climate change and developing strategies to make them more resilient to climate change.
States with adaptation plans in progress					
Delaware	2009			x	In 2009 Delaware began its adaptation planning by convening a workshop bringing together stakeholders to discuss unique threats of sea level rise to each stakeholder. Following this workshop, technical workgroups and an advisory committee were established. The adaptation plan is organized around three key tasks: defining the threats of sea level rise, developing strategies to mitigate damages, and implementing recommendations.
Hawaii	2011			x	Recognizing the need to address climate change adaptation, the Office of Planning held a set of workshops in 2011 and started coordinating a climate change adaptation policy with its partner agencies. Based on these workshops, Act 286 (2012), Climate Change Adaptation Priority Guidelines, was passed by the legislature and signed into law by Governor Neil Abercrombie.
Minnesota	2009			x	In 2009, Minnesota formed the Interagency Climate Adaptation Team (ICAT), which is composed of representatives from multiple state agencies. The ICAT began examining projected climate impacts and released its preliminary report entitled "Adapting to Climate Change in Minnesota" in 2010, making the first step towards building a long-term strategic plan that includes goals and objectives for the state.
New Jersey	2011			x	The New Jersey Department of Environmental Protection partnered with Sustainable Jersey to form the Climate Adaptation Task Force. The Task Force is working on a slate of actions that lead communities through a vulnerability and preparedness self-assessment, and a set of steps to mitigate these potential threats.
Rhode Island	2010		x		The Rhode Island Climate Risk Reduction Act of 2010 (RIGL 23-84) established the Rhode Island Climate Change Commission, which is tasked with studying the projected impacts of climate change and identifying adaptation strategies and mechanisms to mainstream existing state and municipal programs.
Note: the materials presented in this table are primarily based on each state's adaptation planning documents. For states that are still in the process of plan development, I referred to the data of the Center for Climate and Energy Solutions as well as the website of the state environmental department. Because the state of Washington released two planning documents are different time, I describe the development process for each one.					

Table 3-A1c Adaptation Highlights by Impact and Sectors

Panel A - Impacts of Climate Changes Considered in Adaptation Plans

State	Rising temperature	Sea level rise	Coastal erosion	Ocean acidification	Flooding	Storms	Drought	Heat waves	Wildfire	Air pollution	Ecological changes
Alaska	x	x	x	x	x	x	x	x	x	x	x
California	x	x	x	x	x	x	x	x	x	x	x
Colorado	x				x	x	x	x	x	x	x
Connecticut	x	x	x		x	x	x	x	x	x	x
Florida	x	x			x	x	x	x	x		x
Maine	x	x			x	x	x				x
Maryland	x	x	x		x	x	x	x	x	x	x
Massachusetts	x	x	x	x	x	x	x	x	x	x	x
New Hampshire	x	x	x		x	x	x	x		x	x
New York	x	x	x		x	x	x	x		x	x
North Carolina	x	x	x	x	x	x	x	x	x	x	x
Oregon	x	x	x	x	x	x	x	x	x	x	x
Pennsylvania	x	x			x	x	x	x	x	x	x
Vermont	x	x			x	x	x	x		x	x
Virginia	x	x	x		x	x	x	x	x	x	x
Washington	x	x	x		x	x	x	x	x	x	x
Wisconsin	x		x		x	x	x	x		x	x

Panel B- Major sectors considered in adaptation plans

State	Public Health	Agriculture	Coastal management	Water management	Infrastructure	Energy use	Tourism & recreation	Biodiversity	Forestry
Alaska	x	x	x		x	x	x	x	x
California	x	x	x	x	x	x	x	x	x
Colorado		x		x	x	x	x	x	
Connecticut	x	x	x	x	x	x		x	x
Florida	x		x	x	x			x	
Maine	x	x	x	x	x		x	x	x
Maryland	x	x	x	x	x	x		x	x
Massachusetts	x	x	x	x	x	x	x	x	x
New Hampshire	x	x	x	x	x		x	x	x
New York	x	x	x	x	x	x		x	
North Carolina	x	x	x	x	x	x	x	x	x
Oregon	x	x	x	x	x			x	x
Pennsylvania	x	x		x	x		x	x	x
Vermont	x	x		x	x		x	x	x
Virginia	x	x	x	x	x		x	x	
Washington	x	x	x	x	x			x	x
Wisconsin	x	x	x	x	x	x		x	x

Table 3-A1d Highlights on the Overarching Adaptation Strategies in State Plans

State	Intergovernmental coordination and collaboration	Assisting local communities	Mainstreaming (incorporate climate change into existing planning & programs)	Adaptive Management	Advancing climate science research	Public Education, communication and Outreach	Emergency management	Integrating adaptation and mitigation strategies
Alaska	x	x			x	x		
California		x	x	x	x		x	
Connecticut	x	x	x	x	x	x	x	
Colorado	x	x	x		x	x		
Florida	x	x	x		x	x	x	
Maine	x				x			x
Maryland		x	x		x	x	x	x
Massachusetts	x	x		x	x	x	x	x
New Hampshire	x				x	x	x	
New York		x		x	x	x	x	
North Carolina	x	x	x	x	x	x		
Oregon	x		x	x		x		x
Pennsylvania			x	x	x	x	x	x
Vermont								
Virginia	x	x	x		x			
Washington			x		x		x	
Wisconsin		x	x	x	x	x		x

Table 3-A1e Summary on State Adaptation Planning and Their Discussion of Climate Change in Hazard Planning

state	Adaptation planning	Climate adaptation in hazard planning	state	Adaptation planning	Climate adaptation in hazard planning
Alabama	No	1	Montana	No	1
Alaska	Completed	4	Nebraska	No	1
Arizona	No	2	Nevada	No	1
Arkansas	No	2	New Hampshire	Completed	4
California	Completed	4	New Jersey	In progress	3
Colorado	Completed	4	New Mexico	No	1
Connecticut	completed	4	New York	Completed	4
Delaware	In Progress	1	North Carolina	Completed	3
Florida	Completed	3	North Dakota	No	1
Georgia	No	1	Ohio	No	2
Hawaii	In progress	4	Oklahoma	No	1
Idaho	No	1	Oregon	Completed	3
Illinois	No	2	Pennsylvania	Completed	2
Indiana	No	1	Rhode Island	In progress	3
Iowa	No	1	South Carolina	No	2
Kansas	No	2	South Dakota	No	1
Kentucky	No	1	Tennessee	No	1
Louisiana	No	2	Texas	No	2
Maine	Completed	3	Utah	No	2
Maryland	Completed	4	Vermont	Completed	4
Massachusetts	completed	4	Virginia	Completed	2
Michigan	No	3	Washington	Completed	4
Minnesota	In progress	3	West Virginia	No	3
Mississippi	No	1	Wisconsin	Completed	3
Missouri	No	1	Wyoming	No	1

Notes: Scores for climate change discussion in state hazard mitigation plans (Babcock, 2013):
1. no discussion of climate change or inaccurate discussion of climate change
2. minimal mention of climate related issues
3. accurate but limited discussion of climate change and/or brief discussion with acknowledgement of need for future inclusion
4. thorough discussion of climate change impacts on hazards and climate adaptation actions

Appendix 2. Grouping of States by Regions

The regional division is from the 2014 National Climate Assessment (NCA). I have made slight changes by considering Alaska and Hawaii as part of northwest and southwest, respectively. The two states are treated separately in the NCA document.

Northeast
Connecticut
Delaware
Maine
Maryland
Massachusetts
New Hampshire
New Jersey
New York
Pennsylvania
Rhode Island
Vermont
West Virginia

Southeast
Alabama
Arkansas
Florida
Georgia
Kentucky
Louisiana
Mississippi
North Carolina
South Carolina
Tennessee
Virginia

Midwest
Illinois
Indiana
Iowa
Michigan
Minnesota
Missouri
Ohio
Wisconsin

Great Plains
Kansas
Montana
Nebraska
North Dakota
Oklahoma
South Dakota
Texas
Wyoming

Southwest
Arizona
California
Colorado
Nevada
New Mexico
Utah
Hawaii

Northwest
Idaho
Oregon
Washington
Alaska

Appendix 3 Sensitivity Test of Lag Length

In the main paper (Table 3), I include cumulative damage and deaths from major climate-related hazards that have occurred in a state over the past two years. In this appendix, I report the sensitivity tests that are performed using two approaches: (1) I use the cumulative damage and deaths that have occurred in a state over different time periods ranging from the past one to four years; (2) I use a distributed lag model with each year's disaster damage and deaths and gradually increase the year lags. The sensitivity tests suggest that for either damage or deaths-related losses, extreme weather events that occurred in year t-2 have a consistently significant and positive effect on a state's probability to start adaptation planning. In the paper I use the cumulative losses in the past two years instead of a distributed lag model because it is more parsimonious and yields a slightly better goodness of fit.

Table 3-A3a Modeling the effect of cumulative damages over past years

	Past year (1)	Past two years (2)	Past three years (3)	Past four years (4)
Total damages (% of GDP)	-3.338	0.132**	0.0773	0.0320
	(7.088)	(0.0567)	(0.0553)	(0.0588)
The elderly (%)	-0.133	-0.124	-0.116	-0.112
	(0.595)	(0.582)	(0.582)	(0.598)
Agricultural sector (%)	0.158	0.106	0.105	0.112
	(0.382)	(0.401)	(0.402)	(0.400)
Coastline length (thousand miles)	1.037***	1.019***	1.023***	1.015***
	(0.400)	(0.384)	(0.384)	(0.385)
Coastal economy (%)	0.0256**	0.0264***	0.0263***	0.0262***
	(0.0104)	(0.0101)	(0.0101)	(0.0100)
Forest cover (%)	0.0930***	0.0939***	0.0934***	0.0928***
	(0.0257)	(0.0252)	(0.0252)	(0.0253)
Poor infrastructure (%)	-0.103*	-0.104*	-0.104*	-0.104*
	(0.0548)	(0.0543)	(0.0540)	(0.0545)
Median household income in year t-1	0.108**	0.112**	0.115**	0.113**
(thousand dollars)	(0.0507)	(0.0509)	(0.0523)	(0.0530)
Public meeting attendance (%)	0.160	0.175*	0.179*	0.176*
	(0.105)	(0.104)	(0.105)	(0.106)
Democratic governor	1.032	1.055	1.089	1.069
	(1.059)	(1.025)	(1.014)	(1.027)
Democratic legislative control	-0.268	-0.357	-0.375	-0.349
	(1.038)	(1.030)	(1.042)	(1.053)
League of Conservation Voter score	0.0480*	0.0486**	0.0487**	0.0478**
	(0.0248)	(0.0239)	(0.0239)	(0.0240)
Unemployment rate in year t-1 (%)	-0.0597	-0.0636	-0.0619	-0.0585
	(0.183)	(0.183)	(0.183)	(0.182)
Percent adapting states in year t-1 (%)	0.0109	0.0110	0.0109	0.0110
	(0.0151)	(0.0157)	(0.0158)	(0.0156)
t	4.379***	4.487***	4.475***	4.446***
	(1.163)	(1.192)	(1.195)	(1.192)
t^2	-0.373***	-0.381***	-0.379***	-0.378***
	(0.116)	(0.119)	(0.118)	(0.119)
Constant	-25.50***	-26.37***	-26.68***	-26.46***
	(7.171)	(7.387)	(7.621)	(7.732)
Observations	349	349	349	349
AIC	111.3	111.2	111.1	111.4
Log likelihood	-38.66	-38.59	-38.55	-38.69

Note: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3-A3b Distributed lag model of total economic losses

	(1)	(2)	(3)	(4)
Total damage in year t-1	-3.338	-3.661	-3.365	-3.761
	(7.088)	(7.647)	(7.440)	(8.042)
Total damage in year t-2		0.140**	0.145**	0.184**
		(0.0557)	(0.0593)	(0.0750)
Total damage in year t-3			0.0597	0.0595
			(0.0544)	(0.0576)
Total damage in year t-4				-8.258
				(10.14)
The elderly (%)	-0.133	-0.139	-0.135	-0.128
	(0.595)	(0.583)	(0.579)	(0.517)
Agricultural sector (%)	0.158	0.159	0.153	0.131
	(0.382)	(0.381)	(0.385)	(0.348)
Coastline length (thousand miles)	1.037***	1.051***	1.057***	1.144**
	(0.400)	(0.405)	(0.404)	(0.456)
Coastal economy (%)	0.0256**	0.0256**	0.0257**	0.0242**
	(0.0104)	(0.0105)	(0.0106)	(0.0111)
Forest cover (%)	0.0930***	0.0943***	0.0946***	0.0937***
	(0.0257)	(0.0256)	(0.0257)	(0.0233)
Poor infrastructure (%)	-0.103*	-0.104*	-0.105*	-0.0995**
	(0.0548)	(0.0547)	(0.0544)	(0.0486)
Median household income in year t-1	0.108**	0.110**	0.113**	0.113**
(thousand dollars)	(0.0507)	(0.0517)	(0.0534)	(0.0539)
Public meeting attendance (%)	0.160	0.162	0.168	0.151
	(0.105)	(0.105)	(0.107)	(0.114)
Democratic governor	1.032	1.056	1.088	1.017
	(1.059)	(1.041)	(1.026)	(0.971)
Democratic legislative control	-0.268	-0.306	-0.343	-0.467
	(1.038)	(1.053)	(1.070)	(1.109)
League of Conservation Voter score	0.0480*	0.0492**	0.0498**	0.0481**
	(0.0248)	(0.0247)	(0.0246)	(0.0240)
Unemployment rate in year t-1 (%)	-0.0597	-0.0639	-0.0654	-0.116
	(0.183)	(0.184)	(0.185)	(0.199)
Percent adapting states in year t-1 (%)	0.0109	0.0111	0.0111	0.0115
	(0.0151)	(0.0153)	(0.0155)	(0.0161)
t	4.379***	4.417***	4.434***	4.521***
	(1.163)	(1.169)	(1.172)	(1.195)
t^2	-0.373***	-0.375***	-0.375***	-0.382***
	(0.116)	(0.117)	(0.117)	(0.119)
Constant	-25.50***	-25.81***	-26.20***	-25.72***
	(7.171)	(7.321)	(7.593)	(7.377)
Observations	349	349	349	349
AIC	111.3	113.0	114.8	115.7
Log likelihood	-38.66	-38.48	-38.40	-37.86

Note: Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 3-A3c Modeling the effect of cumulative damages over past years

	Past year (1)	Past two years (2)	Past three years (3)	Past four years (4)
Total deaths (hundred)	0.737	0.804**	0.524*	0.428
	(0.514)	(0.329)	(0.294)	(0.297)
The elderly (%)	-0.103	-0.0759	-0.0798	-0.0734
	(0.589)	(0.567)	(0.571)	(0.577)
Agricultural sector (%)	0.116	0.137	0.161	0.187
	(0.394)	(0.381)	(0.372)	(0.367)
Coastline length (thousand miles)	1.024***	1.060***	1.055***	1.058***
	(0.391)	(0.395)	(0.393)	(0.393)
Coastal economy (%)	0.0264***	0.0263**	0.0264**	0.0267**
	(0.0101)	(0.0104)	(0.0103)	(0.0104)
Forest cover (%)	0.0935***	0.0960***	0.0961***	0.0970***
	(0.0253)	(0.0263)	(0.0262)	(0.0267)
Poor infrastructure (%)	-0.104*	-0.108*	-0.108*	-0.109*
	(0.0553)	(0.0562)	(0.0562)	(0.0569)
Median household income in year t-1	0.113**	0.122**	0.123**	0.128**
(thousand dollars)	(0.0504)	(0.0530)	(0.0543)	(0.0570)
Public meeting attendance (%)	0.179*	0.187*	0.186*	0.187*
	(0.102)	(0.103)	(0.104)	(0.106)
Democratic governor	1.054	1.101	1.116	1.145
	(1.036)	(1.009)	(0.994)	(0.989)
Democratic legislative control	-0.312	-0.379	-0.372	-0.386
	(1.017)	(1.043)	(1.032)	(1.028)
League of Conservation Voter score	0.0467*	0.0472**	0.0478**	0.0480**
	(0.0239)	(0.0239)	(0.0241)	(0.0244)
Unemployment rate in year t-1 (%)	-0.0607	-0.0589	-0.0434	-0.0337
	(0.183)	(0.184)	(0.186)	(0.189)
Percent adapting states in year t-1 (%)	0.0111	0.0121	0.0113	0.0114
	(0.0154)	(0.0155)	(0.0156)	(0.0155)
t	4.510***	4.570***	4.512***	4.512***
	(1.207)	(1.214)	(1.207)	(1.216)
t^2	-0.384***	-0.387***	-0.382***	-0.382***
	(0.120)	(0.121)	(0.120)	(0.122)
Constant	-26.70***	-28.00***	-28.05***	-28.56***
	(7.386)	(7.544)	(7.747)	(8.127)
Observations	349	349	349	349
AIC	111.4	110.7	110.7	110.6
Log likelihood	-38.69	-38.37	-38.35	-38.32

Note: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3-A3d Distributed lag model of total deaths

	(1)	(2)	(3)	(4)
Total deaths in year t-1 (hundred)	0.737	0.758	0.784	0.789
	(0.514)	(0.606)	(0.604)	(0.639)
Total deaths in year t-2 (hundred)		0.810***	0.839**	0.869**
		(0.314)	(0.329)	(0.348)
Total deaths in year t-3 (hundred)			0.421	0.444
			(0.281)	(0.295)
Total deaths in year t-4 (hundred)				0.322
				(0.00290)
The elderly (%)	-0.103	-0.0765	-0.0671	-0.0587
	(0.589)	(0.571)	(0.563)	(0.560)
Agricultural sector (%)	0.116	0.138	0.162	0.186
	(0.394)	(0.383)	(0.372)	(0.367)
Coastline length (thousand miles)	1.024***	1.059***	1.073***	1.084***
	(0.391)	(0.400)	(0.403)	(0.405)
Coastal economy (%)	0.0264***	0.0263**	0.0265**	0.0267**
	(0.0101)	(0.0104)	(0.0105)	(0.0106)
Forest cover (%)	0.0935***	0.0960***	0.0973***	0.0988***
	(0.0253)	(0.0262)	(0.0266)	(0.0274)
Poor infrastructure (%)	-0.104*	-0.107*	-0.109*	-0.111*
	(0.0553)	(0.0565)	(0.0572)	(0.0581)
Median household income in year t-1	0.113**	0.122**	0.127**	0.132**
(thousand dollars)	(0.0504)	(0.0530)	(0.0557)	(0.0587)
Public meeting attendance (%)	0.179*	0.187*	0.191*	0.194*
	(0.102)	(0.103)	(0.103)	(0.105)
Democratic governor	1.054	1.101	1.130	1.166
	(1.036)	(1.012)	(0.988)	(0.978)
Democratic legislative control	-0.312	-0.379	-0.393	-0.411
	(1.017)	(1.043)	(1.042)	(1.042)
League of Conservation Voter score	0.0467*	0.0472**	0.0476**	0.0480**
	(0.0239)	(0.0240)	(0.0240)	(0.0242)
Unemployment rate in year t-1 (%)	-0.0607	-0.0583	-0.0484	-0.0400
	(0.183)	(0.186)	(0.188)	(0.191)
Percent adapting states in year t-1 (%)	0.0111	0.0121	0.0119	0.0120
	(0.0154)	(0.0155)	(0.0156)	(0.0156)
t	4.510***	4.565***	4.580***	4.600***
	(1.207)	(1.215)	(1.225)	(1.235)
t^2	-0.384***	-0.387***	-0.387***	-0.388***
	(0.120)	(0.121)	(0.122)	(0.124)
Constant	-26.70***	-27.98***	-28.66***	-29.35***
	(7.386)	(7.633)	(7.963)	(8.317)
Observations	349	349	349	349
AIC	111.4	112.7	114.5	116.3
Log likelihood	-38.69	-38.37	-38.24	-38.14

Note: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix 4 – Full results of Table 4 in the main paper

In this section, I present the coefficient estimates on all the independent variables that are used to produce the regression results in Table 4.

Table 3-A4a Modeling the effect of hazard-specific damages on state-level adaptation planning

	Past two years	*Past three years*	*Past four years*
	(1)	(2)	(3)
Coastal hazards	0.132**	0.0736	0.0307
	(0.0543)	(0.0562)	(0.0582)
Drought, heat waves and wildfire	3.347*	3.361*	3.487**
	(1.831)	(1.844)	(1.765)
Floods and severe storms	-2.489	-0.198	-1.620
	(7.876)	(0.628)	(3.772)
The elderly (%)	-0.107	-0.0942	-0.0977
	(0.585)	(0.583)	(0.581)
Agricultural sector (%)	0.140	0.104	0.102
	(0.399)	(0.394)	(0.393)
Coastline length (thousand miles)	1.056***	1.035***	1.070**
	(0.399)	(0.385)	(0.424)
Coastal economy (%)	0.0256**	0.0262**	0.0249**
	(0.0110)	(0.0103)	(0.0114)
Forest cover (%)	0.0945***	0.0938***	0.0932***
	(0.0263)	(0.0262)	(0.0256)
Poor infrastructure (%)	-0.105*	-0.105*	-0.103*
	(0.0547)	(0.0545)	(0.0538)
Median household income in year t-1	0.116**	0.119**	0.117**
(thousand dollars)	(0.0505)	(0.0523)	(0.0513)
Public meeting attendance (%)	0.173	0.184*	0.174
	(0.109)	(0.106)	(0.111)
Democratic governor	1.126	1.138	1.106
	(1.065)	(1.036)	(1.020)
Democratic legislative control	-0.265	-0.350	-0.392
	(1.098)	(1.063)	(1.044)
League of Conservation Voter score	0.0473*	0.0473*	0.0475**
	(0.0248)	(0.0245)	(0.0231)
Unemployment rate in year t-1 (%)	-0.0488	-0.0491	-0.0751
	(0.187)	(0.187)	(0.196)
Percent adapting states in year t-1 (%)	0.0120	0.0114	0.0126
	(0.0148)	(0.0156)	(0.0146)
t	4.585***	4.606***	4.517***
	(1.272)	(1.278)	(1.194)
t^2	-0.394***	-0.395***	-0.386***
	(0.130)	(0.129)	(0.117)
Constant	-27.05***	-27.55***	-26.83***
	(7.423)	(7.642)	(7.104)
Observations	349	349	349
AIC	114.7	114.8	115.0
Log likelihood	-38.35	-38.38	-38.49

Note: Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Coastal hazards include hurricanes and other coastal events identified by SHELDUS such as storm surges, coastal flooding and coastal erosion. The hazard-specific damage is measured as a percentage of a state' total GDP, and it represents the cumulative damages that have occurred in a state in the past two years, three years and four years, respectively.

Table 3-A4b Modeling the effect of hazard-specific fatalities on state-level adaptation planning

	Past two years (1)	*Past three years* (2)	*Past four years* (3)
Coastal hazards	0.00793***	0.00513*	0.00373
	(0.00251)	(0.00275)	(0.00312)
Heat waves and wildfire	0.0441*	0.0531	0.0303
	(0.0242)	(0.0390)	(0.0307)
Floods and severe storms	-0.384	-0.212	-0.0456
	(0.266)	(0.211)	(0.128)
The elderly (%)	-0.0963	-0.0165	0.0137
	(0.721)	(0.633)	(0.578)
Agricultural sector (%)	0.230	0.363	0.260
	(0.403)	(0.383)	(0.351)
Coastline length (thousand miles)	1.198***	1.267***	1.178***
	(0.442)	(0.458)	(0.445)
Coastal economy (%)	0.0219*	0.0224**	0.0262**
	(0.0117)	(0.0108)	(0.0113)
Forest cover (%)	0.107***	0.115***	0.106***
	(0.0261)	(0.0267)	(0.0263)
Poor infrastructure (%)	-0.113*	-0.117*	-0.120*
	(0.0603)	(0.0611)	(0.0655)
Median household income in year t-1	0.159***	0.185***	0.153***
(thousand dollars)	(0.0591)	(0.0635)	(0.0585)
Public meeting attendance (%)	0.157	0.132	0.184*
	(0.102)	(0.101)	(0.103)
Democratic governor	1.665	1.257	1.122
	(1.394)	(1.017)	(0.960)
Democratic legislative control	-0.00527	-0.376	-0.297
	(0.904)	(0.967)	(0.961)
League of Conservation Voter score	0.0498*	0.0495**	0.0454**
	(0.0259)	(0.0237)	(0.0231)
Unemployment rate in year t-1 (%)	-0.0624	-0.0756	-0.0347
	(0.201)	(0.184)	(0.178)
Percent adapting states in year t-1 (%)	0.00171	0.00530	0.00966
	(0.0166)	(0.0156)	(0.0158)
t	5.176***	5.083***	4.724***
	(1.164)	(1.278)	(1.181)
t^2	-0.421***	-0.415***	-0.393***
	(0.109)	(0.116)	(0.116)
Constant	-31.80***	-33.84***	-31.81***
	(8.369)	(9.929)	(8.754)
Observations	349	349	349
AIC	108.0	111.5	113.5
Log likelihood	-35.00	-36.76	-37.76

Note: Clustered standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Coastal hazards include hurricanes and other coastal events identified by SHELDUS such as storm surges, coastal flooding and coastal erosion. The hazard-specific fatalities measure the cumulative deaths (in people) that are caused by climate hazards within a state in the past two years, three years and four years, respectively.

Appendix References

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