Three Essays on the Economics of Innovation as Adaptation to Climate Change

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see the Statement of Contributions enclosed in the Thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contribution

Chapter 1 and Chapter 3 were developed jointly with my supervisor Dr. Horatiu A. Rus. I have contributed to all stages of research in both chapters. My major contribution in Chapter 1 consisted in the work involved in constructing the model, proving the main results, and simulating models. In Chapter 3, my main contribution was in the review of water governance history, data collection, and empirical analysis.

Abstract

This thesis consists of three chapters on technological innovation as adaptation to climate change.

The first chapter adopts a non-cooperative game theory model to investigate the relationship between adaptation technology and the formation of emission-reducing International Environmental Agreements (IEAs) on climate change. The main contribution to the literature consists of considering countries that are heterogeneous with respect to the benefits and costs of both mitigation of emissions and adaptation. While differences in climate vulnerability are a deterrent for cooperation, this chapter shows that increasing the effectiveness of adaptation in highly vulnerable countries can foster an IEA. Both free-riding on climate change mitigation efforts, and free-riding on adaptation technology among members of an IEA can be reduced by the transfer of adaptation technology within the IEA. A numerical example with parameters estimated from climate change data is employed to simulate stable coalitions and demonstrate how the transfer of adaptation technology reduces free-riding on an IEA.

The second chapter examines the determinants of adaptive innovation aimed at reducing the impact of natural disasters, which are expected to intensify with climate change. Starting from a conceptual model combining perceived risk theory with innovators' profit motive, this study investigates the salience of innovation induced by natural disasters, using a unique dataset that includes related U.S. patent data, and flood, drought, and earthquake damage data for the years 1977 to 2005. To address the potential endogeneity of disaster damage, the control function approach is employed with instrumental variables constructed from disaster intensity measurements. The results show that impact-reducing innovations at the state level respond to national disaster damages in the U.S. In general, the impact of natural disasters is not localized to a state–that is, disaster damage in a state also stimulates innovations in more-distant states. This is in contrast with comparable existing cross-country evidence. The findings in this paper highlight a policy role for the federal government in more effectively spurring impact-reducing innovations nationwide.

With the pressure of economic growth and the impact of climate change, water issues such as water shortage and pollution have substantial impacts on welfare and sustainability. Taking a view of innovation as adaptation to intensified water threats, the third chapter explores the impact of federal and state level regulatory changes with respect to drinking water quality, water pollution and water quantity in the U.S. on the level of relevant technological innovation. Based on a detailed review of relevant legislative acts, a unique dataset covering major amendments and additions to regulated contaminants lists is constructed to capture the changes of water governance in the U.S. in the past 30 years. In addition, technological patents pertaining to water quality and quantity are identified through a comprehensive search process. The empirical results show the impact of water regulations on innovation to be both statistically and economically significant.

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Dedication

To Xinglin and our beloved Avery

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Introduction

According to rapidly accumulating evidence, increasing concentrations of greenhouse gases (GHGs) are a major driver of climate change, with significant economic and non-economic consequences expected (Stern, 2007, 2008; Kousky, 2012). Mitigation policies such as carbon tax and cap-and-trade systems aimed at reducing CO2 emissions, and adaptation measures involving adjustments in ecological, social and economic systems meant to reduce climate change damages are two major approaches to cope with climate change. The recently released the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) titled 'Climate Change 2014: Impacts, Adaptation and Vulnerability' paints a dire picture in terms of the timing and magnitude of the projected impacts around the world. One consequence of the sharper new focus on climate change impacts is that mitigation and adaptation are no longer considered alternative strategies. Increasingly, due to climate hysteresis and other factors, it is becoming accepted that adaptation cannot reduce climate change damages to zero, neither can mitigation entirely revert the underlying trends driving climate change. In this sense, adaptation and mitigation are broadly complementary policies. Indeed, one fact the recently concluded Conference of the Parties (COP) 20 in Lima (December 2014) made exceedingly clear was that a global agreement that is agreed upon by both developing and developed countries would have to include both adaptation and mitigation provisions.

According to Parry (2007), adaptation refers to "adjustments in ecological, social or economic systems to reduce the vulnerability of biological systems to climate change." Examples of adaptation include building dykes and levees to defend against increasing floods, changing crop types, and even relocating population from especially vulnerable areas. In recent years, countries have increasingly considered the role of adaptation technology and invested such innovations to reduce the various impacts of climate change. Since the COP 16 in Cancun, member countries of the United Nations Framework Convention on Climate Change (UNFCCC) have sponsored the Climate Technology Centre and Network (CTCN), which provides technical assistance at the request of member countries and promotes transfers of adaptation technologies.

This thesis addresses climate change adaptation by exploring the interaction of adaptation technology, climate change impacts, domestic policy instruments and international policy cooperation. The first chapter provides a theoretical framework of adaptation technology and its impact on international environmental agreements (IEAs) to mitigate greenhouse gas (GHG) emissions. GHGs are global pollutants, which implies that a country's emissions impose a negative externality on other countries by exacerbating climate change. Therefore, international cooperation, such as the Kyoto Agreement and the Paris Agreement, is required in order to mitigate global GHG emissions effectively. However, ongoing concerns about the feasibility and effectiveness of a global agreement of GHG mitigation bring into focus the need for adaptative measures, such as adaptation technology, as another way to cope with climate change. A non-cooperative game theory model is adopted to investigate the relationship between adaptation technology and the formation of emission-reducing IEAs on climate change, in the context of countries that are heterogeneous with respect to the benefits and costs of both mitigation of emissions and adaptation. The results have some practical implications for international cooperation on mitigation and adaptation. First, technological innovation on adaptation in highly vulnerable countries increases the likelihood of an IEA. Thus, policies directed at helping poor and vulnerable countries adapt to climate change (e.g. the Cancun Adaptation Fund and the Green Climate Fund) can foster cooperation on mitigation. Second, the results show that both free-riding on climate change mitigation efforts, and free-riding on adaptation technology among members of an IEA can be reduced by the diffusion of technological innovation within the agreement. Thus, both mitigation and adaptation can be achieved through an emission-reducing IEA negotiated jointly with a research and development (R&D) hub on adaptation technology which shares innovation among its members.

The second chapter provides insights into the interaction of climate change impacts and adaptation technology, specifically on the subject of natural disasters. As climate scientists suggest that climate change will likely increase dramatically the frequency and intensity of natural disasters such as floods, droughts, heat waves and cold spells (Hallegatte, 2014; IPCC, 2012), technological innovation is an important means to reduce disaster impact and to enhance our adaptive capacity to a changing climate. Nonetheless, very little is known about the impact of past natural disaster damages and the resulting creation of adaptation technology. The second chapter hence focuses on natural disasters and their potentially stimulating effect on technological progress aiming at reducing disaster impacts. First, a framework linking natural disasters and innovation is proposed: disaster damage increases perceived risks and self-protection needs of local communities, and profit motivates potential innovators in both *nearby and more-distant* regions to develop impact-reducing technologies. Then, using a unique dataset that includes U.S. patent data and damage data on floods, droughts, and earthquakes for the years 1977 to 2005, the empirical analysis shows that impact-reducing innovations at a state level respond to national damage for any disaster type in the U.S. Moreover, the impact of natural disasters is not localized to the same state–that is, disaster damage in a state also stimulates innovations in more-distant states. These findings imply a crucial yet currently missing role for the federal government to promote impact-reducing innovations.

With the pressure of economic growth and the impact of climate change, water issues such as water shortage and water pollution have substantial impacts on welfare and sustainability of the economy in its current configuration, as well as for society as a whole. The third chapter is the first to explore the impact of federal and state level regulatory changes with respect to drinking water quality, water pollution and water quantity in the U.S. on the level of relevant technological innovation. Through a detailed review of relevant legislative acts, a unique dataset covering major amendments and additions to regulated contaminants lists is constructed to capture the changes of water governance in the U.S. in the past 30 years. In addition, technological patents pertaining to water quality and quantity are identified through an extensive search process. These data are compiled into a unique dataset including state-level water regulatory changes and water-related innovation. The empirical results show that the impact of water regulations on innovation to be both statistically and economically significant.

Chapter 1

Climate Change Adaptation and International Mitigation Agreements with Heterogeneous Countries

1.1 Introduction

According to rapidly accumulating evidence, increasing concentrations of greenhouse gases is a major driver of climate change, with severe economic and non-economic consequences projected (Stern, 2008; Kousky, 2012). Over the past few decades, jurisdictions across the world have been experimenting with ways to tackle climate change. Mitigation policies such as command and control, carbon tax and cap-and-trade programs aimed at reducing CO_2 emissions, and adaptation measures involving adjustments in ecological and socio-economic systems meant to reduce climate change impacts are two major approaches to address climate change. However, such global efforts have to date been grossly inadequate. The *Working Group II* contribution to the Fifth Assessment Report IPCC titled 'Climate Change 2014: Impacts, Adaptation and Vulnerability' and many other reports paint a dire picture in terms of the timing and magnitude of the projected impacts around the world. One consequence of the sharper recent focus on climate change impacts is that mitigation and adaptation are no longer considered alternative strategies. Due to climate hysteresis and other factors, such as adaptation capability disparities among countries, they are increasingly seen as policy complements (Bayramoglu et al., 2016). Indeed, one fact the recent COPs made exceedingly clear was that a global agreement adhered to by both developing and developed countries would have to include both adaptation and mitigation provisions.

This paper studies the interaction between climate change adaptation technology and incentives to participate in an International Environmental Agreement on GHG emissions mitigation (referred to as an IEA), in the presence of cross-country heterogeneity. We focus on the incentives to free ride for each member, given their specific economic and environmental parameters, and we look at the way these incentives respond to exogenous changes in adaptation technology and net vulnerability to climate change impacts. The importance of accounting for country differences in both benefits and damages from emissions cannot be overemphasized: different levels of development, technology, resource endowment and structure of the economy translate into markedly different economic benefits per unit of carbon emitted, while differences in geography, infrastructure preparedness and institutional capacity also yield substantially different projected economic impacts around the world. Differences among countries are introduced here through four model parameters referring to the benefits and costs of both mitigation and adaptation. To our knowledge, this study is the first to systematically investigate the effect of fully heterogeneous benefits and costs of both mitigation and adaptation on a country's incentives with respect to optimal climate change policy and international cooperation.

GHGs are global pollutants, since a country's emissions impose a negative externality on other countries by contributing to climate change. When countries choose emission levels non-cooperatively, the global GHG emissions exceed the globally efficient level, defined as the fully cooperative outcome where every country chooses its own emissions to maximize global welfare. Thus conceptually, international coordination is required in order to mitigate global GHG emissions effectively. Yet, any emissions mitigation agreement is undermined by the free-rider problem from nonparticipating countries, exacerbated potentially via the 'carbon leakage' effect.[1] Unilateral or plurilateral climate policies adopted by some developed countries will increase the production cost of domestic industries (especially for energy-intensive sectors), and reduce their international competitiveness. In addition, many have argued that the Kyoto Protocol's emission reduction targets and the Paris Agreement's Intended Nationally Determined Contributions are inadequate for slowing down climate change (UNEP, 2012). The ongoing concerns about the feasibility and effectiveness of global IEAs indicate that mitigation of GHG emissions cannot be the only policy response to climate change. Indeed in recent years, countries have increasingly considered undertaking adaptive measures to reduce the impact of climate change.[2]

[1] Unilateral adoption of emission reduction policies can cause carbon-intensive good production to relocate to countries with unrestricted or less stringent environmental policy, and hence increase emissions in those countries.

[2] According to Parry (2007), adaptation refers to adjustments in ecological, social or economic systems

However, asymmetric costs and benefits of both mitigation and adaptation across countries further complicate the relationship between mitigation, adaptation and cooperativeness. In particular, a country with relatively low adaptation costs and/or low exposure to climate change but high mitigation costs may have little incentives to reduce GHG emissions. Thus the heterogeneity of costs and benefits of mitigation and adaptation should result in varying national optimal climate change policies. However, this heterogeneity in the context of mitigation and adaptation efforts is not sufficiently studied in the extant literature. This paper explores the relationship between mitigation and adaptation with heterogeneous countries, and specifically it focuses on the effects of adaptation technology on the formation and stability of an IEA aimed at GHGs mitigation.

It is generally accepted that adaptation cannot reduce climate change damages to zero, neither could mitigation entirely revert the underlying trends driving climate change. In this sense, adaptation and mitigation are broadly complementary policies. In a two-player framework, Eisenack & Kähler (2016) show that considering adaptation may lead to an improved likelihood that unilateral emission reductions can be welfare-improving. Still, as a country invests more in adaptation, it will suffer less damage from climate change, making internalization of the global externality through mitigation less attractive. Moreover, as countries reduce GHG emissions, the speed of climate change may decelerate, making adaptation efforts less worthwhile. Thus, at least if we abstract from non-linearities and high-risk low-probability events, mitigation and adaptation may also be substitutes.

To preview the main results, exogenous technological progress in adaptation creates positive spillovers within the IEA, compared to it being strictly a private good outside of an IEA. Besides the usual free-riding in mitigation, free-riding with respect to adaptation technology emerges among members of an international mitigation agreement. Using two coalition stability concepts, we find that large gaps in vulnerability to climate change prevent the formation of a large IEA. Thus, technological progress in adaptation occurring in (or transferred to) highly vulnerable countries can act as a partial equalizer of vulnerability and can help form a broader international agreement on mitigation. The results also suggest that free-riding in an international mitigation agreement can be reduced through the transfer of new technologies in adaptation to less innovative members. If the R&D of technological progress is funded by members, free-riding with respect to adaptation technology within an IEA can be alleviated.

The interplay between GHG-emission mitigation policies and adaptation activities has not received sufficient attention in the literature to date. The existing work on interna-

to reduce the vulnerability of biological systems to climate change. Examples of adaptation include building dykes and levees to defend against rising sea levels, changing crop types, and even relocating population from vulnerable areas.

tional cooperation on GHG emissions mitigation mostly analyzes the incentives to join emission-reducing IEAs and their stability. A small body of work looking at adaptation and mitigation mostly exploits the trade-off between the two for identical countries. Only a handful of studies allow for heterogeneity across countries in either mitigation or adaptation, and even fewer undertake such analysis in a comprehensive manner.

A substantial part of the existing literature on IEAs analyzes the formation and stability of an IEA using non-cooperative game theory tools. Since there does not exist a supranational institution that can enforce participation in an IEA, it must be *self-enforcing* as a result of the interplay of incentives and interactions among agents. D'Aspremont et al. (1983) define the internal and external stability of a coalition, concepts which are extensively applied in the literature on IEAs. Barrett (1994) studies the stability of an IEA and shows that a self-enforcing IEA may not sustain more than three signatories, or it may sustain a large number of countries, but only when the net gain of moving from noncooperation to full cooperation is very small. Subsequent papers (Barrett, 1997; Pavlova & de Zeeuw, 2013) have similarly reached results that suggest that IEAs that aim to coordinate GHG emissions mitigation may not achieve much, and the real world experience to date seems to confirm these pessimistic findings.[3] In a recent paper, Battaglini & Harstad (2016) show how coalitions can be enlarged when considering technological investments in green technologies under incomplete contracting. When the agreement focuses on internalizing the positive externality of investments in clean technology R&D rather than on mitigation, El-Sayed & Rubio (2014) show that a small stable coalition is feasible. However, clean technologies aimed at reducing carbon emissions do not necessarily enhance cooperation on mitigation. As demonstrated in Benchekroun & Chaudhuri (2015), the adoption of cleaner technologies does not always improve the odds of achieving a stable coalition.[4]

Only a small number of recent papers look explicitly at the interaction between adaptation and mitigation. The literature on adaptation to climate change in this context can be categorized into two streams. The first highlights the trade-off between mitigation and adaptation across countries. The second stream incorporates adaptation in integrated assessment models (IAMs) and simulates the interaction between adaptation and mitigation. The present paper is in line with the first body of work, but explores the relationship between adaptation and coalition formation. Benchekroun et al. (2014) develop a model based

[3] e.g. despite Kyoto's relatively large membership, only a few signatories actively curbed emissions.

[4] Several ways to overcome this predicament have been explored, notably Nkuiya et al. (2015) show how endogenous uncertainty can increase IEA participation. Focusing on intellectual property rights (IPRs) of clean technologies, Goeschl & Perino (2017) show that a global system of IPRs on clean technologies can undermine the size and the abatement goal of an IEA. Finus & Rübbelke (2013) consider several models and show that while accounting for ancillary benefits of mitigation may increase the likelihood of reaching an international agreement, the size of the resulting coalition may in fact be smaller.

on Barrett (1994) with adaptation as a policy instrument additional to mitigation. With identical adaptation and mitigation across countries, more effective adaptation measures may diminish a member's incentive to leave an emission-reducing IEA and lead to larger stable coalitions. Thus, while adaptation and mitigation are normally considered substitutes, their conclusion is that adaptation efficiency increases and IEAs on mitigation are complements. We generally confirm these results in this paper, while also outlining the role of cross-country heterogeneity with respect to vulnerability. Our framework also allows us to be more precise in describing the effects of technological progress in adaptation, depending on the membership status and idiosyncratic characteristics of the innovation adopter. While in reality costs and benefits of both mitigation and adaptation differ widely across countries, most studies in the sizeable literature on IEAs assume homogeneous agents (i.e. countries are symmetric). The body of work considering heterogeneous countries is comparatively much smaller. Close to our focus, Lazkano et al. (2016) assume two types of adaptation costs and analyze the incentives to join an IEA on mitigation with and without carbon leakage. The article shows that considering adaptation may not discourage the formation of a mitigation agreement, and detail cases when exogenous reductions in the cost of adaptation differences among countries have positive or negative effects on cooperation. A recent working paper by Bayramoglu et al. (2016) also brings together climate change mitigation and adaptation to analyze conditions for a more successful climate agreement. While their work generally follows the assumption of ex-ante symmetric players, some of their results around the order of adaptation and mitigation and the cooperation-enhancing potential of adaptation could be extended to asymmetric players. Our focus on adaptation technology, on the specific ways in which countries differ with respect to their vulnerability to climate change impacts, as well as on the 'club-goods' nature of adaptation technology improvements within an IEA makes our work complementary to theirs.

To summarize, the main contribution of the paper is to be one of the first to allow for the full set of mitigation and adaptation parameters to be country-specific, as it studies the incentives of countries to join international GHG emissions mitigation coalitions. We obtain results on the likelihood of cooperation which are contingent on these country-specific characteristics and which can be used to inform policy. For example, technology transfers aimed at reducing country-specific vulnerability to climate impacts are shown to be cooperation-enhancing. We are also flexible in terms of the timing of adaptation, by studying cases in which it takes place both prior to and simultaneous with (or, equivalently, subsequent to)[5] the choice of emission reductions. Additionally, we extend our model to show how shared technological advances in adaptation among the members of an IEA has the potential to increase cooperation, and we derive conditions involving the

[5] Please see discussion in the online appendix. http://personal.uwaterloo.ca/h254li/

assumed country-specific parameters for the enhanced potential of such coalitions. Finally, unlike the received literature, numerical simulations we use to solve for the stable coalitions employ empirically estimated parameters, based on a dataset assembled for this purpose. What in our view constitute the paper's chief limitations, namely the exogeneity of technical progress and the essentially static nature of the game - are left as topics of future research.

The rest of the paper proceeds as follows. The model with heterogeneous agents is presented in section two. Section three characterizes the coalition equilibrium of the model. The incentive to participate in an IEA will be analyzed in section four. Section five tackles coalition stability, section six presents the numerical simulation, while section seven summarizes the main results and provides some directions for future work.

1.2 The Model

We model a non-cooperative IEA membership game, widely considered to be both more realistic and more general than cooperative games.[6] The game structure is based on McGinty (2007) and Benchekroun et al. (2014), and it includes a standard coalition formation game theory setting which we augment with heterogeneous costs and benefits of adaptation across countries. In this paper the full set of parameters characterizing both mitigation costs (i.e. benefits of emissions) and net damage costs (including natural vulnerability and adaptation effectiveness) are assumed to be country-specific.

Let $N = \{1, ..., n\}$ denote the set of all countries. Emissions e_i of a global pollutant (e.g., a GHG) is the by-product of consumption and production activities of each country i. While most of the literature confines analysis to positive emission choices, we allow for negative net country emissions, which would correspond to processes like carbon sequestration.[7] Global emissions of the global pollutant are aggregated over all countries,

[6] A literature survey by Finus (2008) states that 'the potential for explaining real world phenomena of IEAs is much higher for the non-cooperative than for the cooperative approach,' due to the absence of a clear supranational authority on which cooperative models are usually reliant on, the fact that non-cooperative models separate coalition formation from stability considerations and are able to replicate some cooperative assumptions and outcomes.

[7] Such 'negative emissions' are consistent with the 2016 Paris Agreement, which projects the need for negative emissions in order to keep the temperature increase under 2°C. An additional technical advantage of allowing $e_i < 0$ here is that we do not need to restrict how different countries are from each other. Otherwise, in order to keep e_i positive, one needs to assume country i cannot be 'too small' or 'too vulnerable' compared to the rest of the world, and thus artificially tilting the table towards cooperation. Still, for simplicity of exposition, we do assume that the *combined* world emissions are positive, i.e. $E > 0$.

$E \equiv \sum_{i=1}^{n} e_i$. For country i, the emissions from the rest of the world are denoted by $E_{-i} \equiv \sum_{j \neq i \in N} e_j$.

Let $B_i(e_i)$ represent the benefit that country i derives from its own emissions-generating production and consumption activities:

$$B_i(e_i) \equiv e_i \left(\alpha_i - \beta_i \frac{e_i}{2} \right), \tag{1.1}$$

with $\alpha_i, \beta_i > 0$. The marginal benefit of emissions is given by $\frac{dB}{de_i} = \alpha_i - \beta_i e_i$, and hence the benefit $B_i(e_i)$ is monotonically increasing over $(-\infty, \overline{e_i}]$, where the maximum emissions level is defined as $\overline{e_i} \equiv \frac{\alpha_i}{\beta_i}$.[8] The marginal benefit of emissions diminishes with the amount of emissions, since $\frac{d^2B}{de_i^2} = -\beta_i < 0$.

While the benefits of emissions are private, the effects of emissions represent a global public bad: the damage is imposed to all countries, albeit differentially. The actual damage to country i is assumed to be a convex function of global emissions and country-specific vulnerability (v_i) and adaptation (θ_i) parameters:

$$D_i\left(E, a_i\right) \equiv \frac{v_i}{2} E^2 - \theta_i a_i E, \tag{1.2}$$

with $v_i, \theta_i > 0$. The first term in (1.2) is the damage caused by global emissions, with v_i denoting the country's natural vulnerability to climate change. This 'ex-ante' vulnerability is an exogenously given parameter, characteristic to each country, and should be distinguished from a country's actual or 'ex-post' vulnerability to climate change impacts, which takes into account the actual equilibrium level of emissions and the optimal level of adaptation. The second term in (1.2) represents the country-specific damage-reduction effect or 'benefit' from adaptation. The adaptation level chosen by country i is denoted by a_i and is assumed to be private to that country: it reduces the climate-induced damage for country i only. θ_i denotes the effectiveness of adaptation. While expression (1.2) resembles the damage function adopted in Benchekroun et al. (2014) in the way in which adaptation enters the damage function, we differ in that *both* the vulnerability and the adaptation parameters are heterogeneous across countries.

Note three main features of the the damage function defined in (1.2). First, whenever there are positive damages from climate change, which we assume in order to avid a

[8] This ceiling ensures that higher emissions - as a proxy for a higher scale of beneficial consumption and/or production activities - continue to bring about positive marginal benefits. The condition under which individual country emissions are in this range is provided in 1.4 below.

trivial solution,[9] it is strictly increasing and convex in global emissions and decreasing in adaptation. Second, the marginal damage from emissions $\frac{\partial D(E,a_i)}{\partial E} = v_i E - \theta_i a_i$ is decreasing in adaptation. Third, the marginal benefit of adaptation $-\frac{\partial D(E,a_i)}{\partial a_i} = \theta_i E$ increases with global emissions: the higher the global emissions, the more valuable adaptation activities.

The convex cost of adaptation for country i is:

$$C_i\left(a_i\right) \equiv \frac{c_i}{2} a_i^2, \tag{1.3}$$

where $c_i > 0$, with differences in adaptation costs across countries captured by parameter c_i. Technological progress in adaptation can affect both the effectiveness and the cost of adaptation activities: either θ_i rises and/or c_i drops.[10]

Climate change is costly for an economy in terms of both direct net damages given its adaptive measures $D_i(E, a_i)$, and in terms of the cost of those adaptive efforts. We call this 'the total climate cost': $CC_i(E, a_i) \equiv D_i(E, a_i) + C_i(a_i)$, and by using (1.2) and (1.3) and with a_i optimally chosen, the marginal climate cost can be written as $MCC_i = E\left(v_i - \frac{\theta_i^2}{c_i}\right)$. Notice that if adaptation is very effective and/or its cost is very low, this marginal cost of climate change can turn negative, in what might be termed 'profitable over-adaptation'. To rule out this less interesting scenario, the following is assumed to hold:

$$v_i > \frac{\theta_i^2}{c_i}. \tag{1.4}$$

Technically, the purpose of this assumption is twofold. First, the marginal cost of global emissions for country i, as derived in optimization problems under different cooperation scenarios in Section 1.3, is always positive. Second, this also guarantees a positive marginal benefit from emissions at the optimal emission level. Therefore, the optimal emissions level of a country i is always smaller than its maximum emission level: $e_i \leq \overline{e_i} \equiv \frac{\alpha_i}{\beta_i}$.

The social welfare of country i is determined as the benefits of emissions, net of climate-induced damages given own adaptation efforts, and net of the cost of these efforts, where

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[9] $D > 0 \iff E > 2\theta_i a_i / v_i \Rightarrow E > \theta_i a_i / v_i \iff D_E > 0$.

[10] We depart here from Benchekroun et al. (2014) in using both θ and c as parameters. While both essentially represent differences in adaptation across countries, economies may in fact differ from each other with respect to either one, or both. The two adaptation parameters also yield different implications for both private investment and policy, which may target the effectiveness of adaptation θ and the costs of adaptation c separately.

the last two terms are jointly defined above as the cost of climate change:

$$w_i\left(e_i, a_i, E\right) \equiv B_i(e_i) - D_i\left(E, a_i\right) - C_i\left(a_i\right) = B_i(e_i) - CC_i(E, a_i).^{11} \tag{1.5}$$

1.3 Equilibrium

We consider a model based on a two-stage, simultaneous-move, open membership game.[12] In the first stage, countries choose whether to participate in the international agreement on abatement, and in the second stage they concomitantly choose their level of emissions/abatement and adaptation. While some version of this model is common in the literature, a brief discussion of these assumptions and some alternatives appears warranted at this point.

First, it should be noted that we assume a monocentric setting, i.e. that a single (global) agreement is under consideration, as opposed to several competing ones.[13] Second, any country is eligible to join, i.e. there is no exclusivity clause. Third, countries decide on their participation in the agreement simultaneously, i.e. the Cournot-Nash assumption. In reality there is a sequential element to many agreements, whereby a small group of countries may initiate a regime that subsequently incorporates new members. Finus (2008) reviews the sub-literature that takes a sequential approach and points out that this modelling choice is not clearly superior, as it involves a tradeoff between increased realism and loss of explanatory power. Moreover, these sequential games assume identical countries. In our heterogeneous countries setup, allowing for a sequential structure of the game would require endogenizing the order in which countries decide on their participation, substantially increasing the array of strategic options and further diluting the results.[14]

Fourth, players also make the abatement and adaptation decisions simultaneously, also a widely used assumption in the literature.[15] This assumption is less restrictive than it may appear at first. According to Zehaie (2009), this scenario is equivalent to one in which the (private) adaptation decisions are made subsequent to (global) abatement choices, as also pointed out in Benchekroun et al. (2014) and shown more generally in Bayramoglu et al.

[11] While all functions are country-specific, as indicated so far by the i subscripts, we omit these in the following analysis, in order to simplify notation.

[12] See Finus (2008), p. 35 for a detailed taxonomy of these models.

[13] A few studies discuss that multiple agreements can be an alternative to a single agreement on climate change, such as Carraro (1999) and Asheim et al. (2006).

[14] See Finus (2008), p. 49-51 for a discussion of existence of equilibrium and other issues in this context.

[15] See Carraro & Siniscalco (1993), Barrett (1994), Pavlova & de Zeeuw (2013)

(2016).[16] However, there is another interesting possibility in our context. Given that many adaptation projects require substantial infrastructure investment,[17] which may take a long time to complete, it is likely for some prospective IEA members to have already committed significant amounts of funds to such purposes *before* a mitigation agreement is reached. De Bruin et al. (2011) examine the effects of proactive adaptation on the size and welfare of the stable coalitions with calibration of a three-stage model. Proactive adaptation can be applied strategically by one or more countries to affect the IEA outcome. We look at this option in the appendix and as expected, countries have lower incentives to join the coalition (more incentive to free ride) if they have already decreased their *de facto* vulnerability via adaptation.[18] Equivalently, should an IEA be formed eventually, countries over-adapt.

Lastly, in order to keep the model comparable to our benchmarks, we do not allow for side-payments. It is well known that transfers, dispute settlement and monitoring mechanisms can extend cooperation,[19] however we aim to focus here on the main incentives in the absence of such schemes. Moreover, the practical logistics of such transfers are problematic in a world in which the most vulnerable countries have the most to benefit from an IEA, are also the ones who benefit the least from emissions and are often among the poorest, would conceivably have to compensate the richer, less vulnerable industrialized countries in order to induce them to join the IEA.[20] Transfers have rarely been used in existing IEAs due to moral hazard issues between donors and recipients, according to Finus (2000). Nevertheless, if allowing for country heterogeneity with respect to all dimensions related to abatement and adaptation increases the chances of cooperation, an optimally designed transfer scheme could further improve those odds.

We first studied the two polar opposite cases of *no cooperation* and of *full cooperation*, and the complete results are provided in A.2. While these two cases are relevant, they are examined in the existing literature and are particular applications of the more general *partial cooperation* case. Here we proceed directly with the general case of a coalition of any number of members.

[16] See Benchekroun et al. (2014), p. 4. and Bayramoglu et al. (2016), p. 15.

[17] Note that adaptation through infrastructure investments may be emission-generating as well, although here we do not highlight this aspect, for simplicity.

[18] Please see the discussion in the online appendix.

[19] See for instance Carraro & Siniscalco (1993).

[20] Several such transfer schemes - including ‘pragmatic’ ones and some including ethical considerations - are discussed in Finus (2008), p. 42-44. It should be noted that full cooperation is still not achievable under most of these transfer mechanisms.

1.3.1 Coalition Formation

Let S denote the set of signatories of a coalition, or an IEA, and let O denote the set of non-signatories. Let $E^O(S)$ denote the aggregate emissions by non-signatories, and $E^O_{-i}(S)$ the emissions by all non-signatories other than i. Let $E^S(S)$ denote the aggregate emissions by the set of signatories and $E^S_{-j}(S)$ the emissions by all signatories other than j. Let $E^N(S) \equiv E^O(S) + E^S(S)$ be the global emissions, given the existence of a coalition S.

Non-signatories

A non-signatory i behaves like a singleton and maximizes its payoff, given other countries' emissions:

$$\max_{e_i, a_i} w\left(e_i, a_i, E^N\right) = B(e_i) - D\left(E^N, a_i\right) - C\left(a_i\right). \tag{1.6}$$

The first order conditions are given by: $\alpha_i - \beta_i e_i - v_i\left(E^O + E^S\right) + \theta_i a_i = 0$ and $\theta_i\left(E^O + E^S\right) - c_i a_i = 0$. While adaptation is a private good, an increase in the amount of adaptation in a country a_i - other things equal - allows it to have higher equilibrium emissions, which then generate spillover effects for all other countries, impacting their own optimal adaptation and emission decisions.

The best response emissions and adaptation functions for a non-signatory i are given as follows,

$$e_i = \frac{\alpha_i - \Phi_i\left(E^S + E^O_{-i}\right)}{\beta_i + \Phi_i}, \tag{1.7}$$

$$a_i = \frac{\theta_i}{c_i}\frac{\alpha_i + \beta_i\left(E^S + E^O_{-i}\right)}{\beta_i + \Phi_i}, \tag{1.8}$$

where $\Phi_i \equiv v_i - \frac{\theta_i^2}{c_i}$ is the net vulnerability in the presence of adaptation, and is always positive, given (1.4). As a result of technological progress in adaptation in country i, θ_i rises and/or c_i drops and country i's net vulnerability decreases. Substituting e_i and a_i from (1.7) and (1.8) into (1.2), we obtain the net marginal damage from emissions: $\frac{dD(E)}{dE} = \Phi_i E^N$.

From (1.7), the aggregate emissions best response function of all non-signatories $E^O(S)$, given the aggregate emissions by signatories E^S, is given by the following:

$$E^O(S) = \frac{\overline{E}^O - \Psi^O E^S}{1 + \Psi^O}, \tag{1.9}$$

where $\overline{E}^O \equiv \sum\limits_{i \in O} \bar{e}_i$, $\Psi^O \equiv \sum\limits_{i \in O} \Psi_i$, and $\Psi_i \equiv \frac{\Phi_i}{\beta_i}$.

Signatories

Each signatory to the agreement j maximizes the joint welfare of the coalition S, given the emissions by non-signatories E^O.

$$\max_{e_j, a_j} \sum_{j \in S} w\left(e_j, a_j, E^N\right) = \sum_{j \in S} \left[B(e_j) - D\left(E^N, a_j\right) - C\left(a_j\right)\right] \tag{1.10}$$

The best response functions for a signatory j are given by,

$$e_j = \frac{\alpha_j - \Phi^S\left(E^S_{-j} + E^O\right)}{\beta_j + \Phi^S}, \tag{1.11}$$

$$a_j = \frac{\theta_j}{c_j} \frac{\alpha_j + \beta_j\left(E^S_{-j} + E^O\right)}{\beta_j + \Phi^S}, \tag{1.12}$$

where $\Phi^S \equiv \sum\limits_{j \in S} \Phi_j$. Using (1.9), (1.11) and (1.12), global and individual emissions levels can be derived. The emission level of a non-signatory and a signatory are given as follows:

$$e^O_i = \overline{e_i} - \Psi_i E^N = \overline{e_i} - \frac{\Psi_i}{1 + \Psi^O + \Psi^S}\overline{E}, \tag{1.13}$$

$$e^S_j = \overline{e_j} - \Psi^S_j E^N = \overline{e_j} - \frac{\Psi^S_j}{1 + \Psi^O + \Psi^S}\overline{E}, \tag{1.14}$$

where $\Psi^S_j \equiv \frac{\Phi^S}{\beta_j}$ and $\Psi^S \equiv \sum\limits_{j \in S} \Psi^S_j$. $\overline{E} \equiv \sum\limits_{k \in N} \overline{e_k} = \sum\limits_{k \in N} \frac{\alpha_k}{\beta_k}$ is the maximum level of world's emissions. Note that Φ_i is the rate of change for the marginal damage from emissions net of adaptation, while β_i is the rate of change for marginal benefit of emissions. Therefore, Ψ_i is the relative rate of change for marginal damage to marginal benefit. A non-signatory's emission level, as given by (1.13), is equal to its maximum emission level minus its abatement level. In the second term, Ψ_i is a country-specific 'abatement indicator': a country with a larger Ψ_i (i.e. larger Φ_i and/or smaller β_i) abates more. A signatory's emissions in (1.14) can be interpreted in a similar way. Nonetheless, the abatement indicator of a non-member, Ψ_i, is based on its own net vulnerability Φ_i, while for a member, its abatement indicator Ψ^S_j depends on the aggregate vulnerability of the coalition Φ^S. Hence a member always abates more than a comparable non-member.[21]

The world's total emissions is the sum of E^S and E^O, given a coalition S:

$$E^N(S) = E^S(S) + E^O(S) = \frac{\overline{E}}{1 + \Psi^O + \Psi^S}. \tag{1.15}$$

If a non-signatory i joins coalition S, the denominator of the world emissions increases by $(\frac{\Phi^S}{\beta_i} + \Phi_i \sum\limits_{j \in S} \frac{1}{\beta_j})$. If the IEA contains a large number of members, the world emission level could fall by a substantial amount. Thus, the size of the coalition is crucial to the impact of an IEA.

Finally, the adaptation level of any country i is given by,

$$a_i = \frac{\theta_i}{c_i} E^N, \forall i \in N. \tag{1.16}$$

With the assumption of heterogeneous countries, we are able to identify the different impacts of exogenous technological progress in adaptation being adopted in non-member and in member countries as follows:

Proposition 1. *Given an existing coalition S, the impact of exogenous technological progress in adaptation depends on whether it is adopted in a non-member or a member country:*

i. given adaptation technological progress in a non-member of the coalition, the country will pollute more and adapt more in equilibrium. All other non-members and all members respond by reducing emissions and adapting more;

ii. given adaptation technological progress in a coalition member, all members will pollute more and adapt more in equilibrium. Every non-member responds by reducing emissions and adapting more in equilibrium.

Proof. See A.1.1 □

Technological progress in adaptation in a country that is not a member of the coalition reduces its 'ex-post' or actual vulnerability to climate change, and that country's optimal emission level rises as a result. This is an apparent counter-intuitive effect, in

[21] This result is standard in the literature. Nonetheless, one opposite case is demonstrated in Goeschl & Perino (2017), where a member may abate less than a non-member country in the presence of intellectual property rights of new clean technology.

which a decrease in vulnerability seems to be associated with an increase in adaptation. Note, however, that the causation runs in the following direction: the country becomes less vulnerable as a result of undertaking more adaptation, which is now either cheaper or more effective (or both) and that leads to the ensuing decrease in net vulnerability (Φ_i). Nevertheless, emission levels increase in the country where adaptation technology progress occurs. However, the externality of its increased emissions is imposed to other countries, both signatories and non-signatories, which will respond by reducing their emissions, in order to partially offset the damages. Thus, emission levels are *strategic substitutes*. However, given that the coalition behaves like one representative agent, technological progress in adaptation in one member country reduces the overall vulnerability of the coalition, and all members can afford higher equilibrium emission levels. Members' emissions choices are *strategic complements* in the presence of new adaptation technology adopted in a member country.

Proposition 2. *Given an existing coalition S, technological progress in adaptation is a private good in non-member countries; however, it induces a positive externality in a coalition.*

i. If technological progress in adaptation is adopted in a non-member country, it benefits from raising its emission level. The negative externality of emissions is imposed to other countries.

ii. If technological progress in adaptation is adopted in a member country j, it generates a positive externality for other members; their welfare increases when $\Phi_k\beta_k < \frac{\Phi^S}{\sum_{j\in S}\frac{1}{\beta_j}}\left(1+\sum_{i\in O}\frac{\Phi_i}{\beta_i}\right)$, $k \neq j \in S$, and the coalition's welfare always rises. A non-member's welfare decreases.

Proof. See A.1.2 □

An interesting implication of Propositions 1 and 2 is that unlike when it occurs outside an IEA, technological progress in adaptation induces a positive externality inside the coalition. Moreover, opposite to the case for non-members, adaptation technology progress in a member country j is not always beneficial to j, that is, the sign of the welfare effect $\frac{dw(e_j^S)}{d\Phi_j}$ depends on the members' characteristics. Hence inside a coalition, technological progress in adaptation in a member country may not always be adopted, even though such progress is always gainful for the coalition as a whole. An intriguing further implication is that non-member countries are more in favor of adopting technological progress in adaptation, while member countries may suppress the adoption of such progress. Furthermore, since technological progress in adaptation is always beneficial to a country outside the coalition, a member country experiencing negative welfare effects following this technological progress is more likely to back out of the IEA.

Another important implication of Proposition 2 is that the location of innovation adoption on adaptation is crucial to the welfare gain of the coalition. Note that $\frac{dw(e_k^S)}{d\Phi_j} < 0$ if $\Phi_k \beta_k < \frac{\Phi^S}{\sum_{j \in S} \frac{1}{\beta_j}} \left(1 + \sum_{i \in O} \frac{\Phi_i}{\beta_i}\right)$, where $k \neq j \in S$. Thus, a member country k with a high benefit from emissions (low β_k) and less vulnerable to climate change (low Φ_k) is most likely to gain from technological progress in adaptation occurring in another member country j. On the contrary, highly vulnerable and less developed member countries are more likely to see welfare reductions if other members experience technological progress in adaptation: such members suffer significantly more damages from higher level of global emissions, but the gain of increased own emissions is limited. Thus, technological progress in adaptation is not always welfare-increasing for all members. Nevertheless, since $\frac{dw(e_j^S)}{d\Phi_j} < \frac{dw(e_j^S)}{d\Phi_k}$, with $k \neq j \in S$, a member always gains more if technological progress in adaptation occurs in that country. The reason is that technological progress in adaptation in the adopting country reduces its actual vulnerability to climate change while other member countries' vulnerability is not affected. In the (admittedly less likely) scenario that the technological progress in adaptation occurs in highly vulnerable less developed countries, the welfare of all individual members increases, and their incentives to cooperate via an IEA become stronger. In contrast, from Proposition 2, a non-member's welfare decreases if a member sees technological progress in adaptation. Thus, non-members will have lower incentives to continue to be free riders. In summary, the location of technological progress in adaptation is crucial to the welfare gains and distribution, hence to the success of an IEA. This finding suggests a role for technological transfers as part of the negotiations leading to an agreement.

Our results so far have focused on vulnerability-reducing technological change. For completeness, we now look at some comparative statics with respect to benefit function parameters. A country's marginal cost of abatement (or marginal benefit of emissions) may also increase exogenously, e.g. due to new CO_2 intensive mineral discoveries, due to shifts in the production structure of the economy induced by international trade, or due to general production process, factor-augmenting, or end-of-pipe innovation (Amir et al., 2008). Without cooperation, its equilibrium emissions will increase - *ceteris paribus* - with implications for the rest of the world. The following intermediary result illustrates the effects of free-riding in the presence of a global externality:

Lemma 1. *If country i's marginal benefit of emissions shifts up (i.e. α_i rises) - other things equal -, its emissions level will increase. All other countries respond by reducing emissions and adapting more, and global emissions rise. If country i's marginal benefit of emissions becomes flatter (i.e. β_i falls) - other things equal -, its emissions increases. All other countries respond by reducing emissions, yet global emissions increase.*

Proof. See A.1.3 □

The benefit of emissions occurs privately to a country regardless of its membership status. Thus the impact of exogenous changes in the benefit side is similar across countries regardless of the existing coalition and a country's membership status. Nevertheless, the increase in emissions of signatories is less pronounced than for non-signatories, following an exogenous rise in the marginal benefit of emissions.

Lemma 2. *If no country joins the coalition, i.e. $S = \varnothing$ and $O = N$, then $E^N = E$, which is the non-cooperative global emission level. If all countries are members of the coalition, $E^N = E^G$, which is the global emissions level in the presence of the grand coalition. Global emissions given a coalition of N signatories are between the non-cooperative and full-cooperative levels: $E^G \leq E^N \leq E$, and their level falls with the size of the coalition. Adaptation levels are also between the non-cooperative and full-cooperative levels: $a_i^G \leq a_i^N \leq a_i$ for $\forall i \in N$.*

Proof. See A.1.4 □

1.4 Stability

Since no supranational institution that can enforce participation exists, an IEA must be *self-enforcing* as a result of the strategic behaviour of agents. A substantial part of the existing literature on IEAs (Barrett, 1994, 1997; McGinty, 2007; Pavlova & de Zeeuw, 2013) analyzes the formation and stability of an IEA using the internal and external stability conditions defined in D'Aspremont et al. (1983): a coalition is internally stable if no member wants to leave it, and it is externally stable if no non-member wants to join. Most of the studies analyze stability of an IEA assuming limited types of agents and no role for adaptation. With heterogeneous countries, we find that large gaps in vulnerability prevent the formation of a coalition, since in that case, less vulnerable members are better off leaving the coalition. The internal stability condition is violated, and a stable coalition cannot be formed with significant disparity of vulnerability among countries. This result implies technological progress in adaptation in highly vulnerable countries can help reduce the gaps, and hence fosters cooperation in climate change mitigation.

Normally three conditions need to be satisfied at a coalition equilibrium: profitability, internal stability and external stability (Hoel, 1992; Finus, 2001; Carraro, 2003). Since internal stability implies profitability in our model, we focus here on internal and external stability conditions.[22]

1.4.1 Cooperative Incentives and Free-riding Incentives

Let $S\backslash\{j\}$ denote the resulting coalition when signatory j leaves S, and let $S\cup\{i\}$ denote the coalition when non-signatory i accedes to S. For a given coalition S, a signatory j's emission and the world emission levels are given by (1.14) and (1.15). Using (1.13) and (1.15), a former signatory's emissions if it leaves the IEA and the world's total emissions are as follows:

$$\begin{aligned} e_j^O(S\backslash\{j\}) &= \overline{e_j} - \frac{\Psi_j}{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})}\overline{E} && (1.17) \\ E^N(S\backslash\{j\}) &= \frac{\overline{E}}{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})}, && (1.18) \end{aligned}$$

where $1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\}) = 1+\Psi^O+\Psi^S+2\Psi_j-\Psi_j^S-\Phi_j\sum_{k\in S}\frac{1}{\beta_k}$, $j\in S$.

Define the *cooperative incentive* Γ^S of a member country j as its current welfare less its potential welfare as a non-signatory. From (1.14), (1.15), (1.17) and (1.18):

$$\begin{aligned} \Gamma_j^S(S) &= w_j^S(S) - w_j^O(S\backslash\{j\}) \\ &= \frac{\overline{E}^2}{2}\left[\frac{\Phi_j\Psi_j+\Phi_j}{(1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\}))^2} - \frac{\Phi^S\Psi_j^S+\Phi_j}{(1+\Psi^O+\Psi^S)^2}\right]. && (1.19) \end{aligned}$$

For a given coalition S, a non-signatory i's emission and the world emission levels are given by (1.13) and (1.15). Using (1.14) and (1.15), a former non-signatory i's emissions

[22] The profitability condition is explored in the online appendix, as it can be applied to a scenario where an IEA can only be formed when all pivotal countries participate. With some pivotal countries, an IEA will either be formed with the participation of these countries or not be formed at all. Hence participation of pivotal countries depends on profitability. participate. The result implies a large gap in adaptation among pivotal countries may prevent the emergence of an IEA.

if it joins the IEA and total global emissions are as follows:

$$e_i^S(S \cup \{i\}) = \overline{e_i} - \frac{\Psi_i^S + \Psi_i}{1 + \Psi^O(S \cup \{i\}) + \Psi^S(S \cup \{i\})}\overline{E} \tag{1.20}$$

$$E^N(S \cup \{i\}) = \frac{\overline{E}}{1 + \Psi^O(S \cup \{i\}) + \Psi^S(S \cup \{i\})}, \tag{1.21}$$

where $1 + \Psi^O(S \cup \{i\}) + \Psi^S(S \cup \{i\}) = 1 + \Psi^O + \Psi^S + \Psi_i^S + \Phi_i \sum_{k \in S} \frac{1}{\beta_k}$, $i \in O$.

Define the *free riding incentive* Γ^O of a non-member country i as its current welfare less its potential welfare when becoming a signatory of a coalition.

$$\begin{aligned} \Gamma_i^O(S) &= w_i^O(S) - w_i^S(S \cup \{i\}) \\ &= \frac{\overline{E}^2}{2}\left[\frac{(\Phi^S + \Phi_i)(\Psi^S + \Psi_i) + \Phi_i}{(1 + \Psi^O(S \cup \{i\}) + \Psi^S(S \cup \{i\}))^2} - \frac{\Phi_i \Psi_i + \Phi_i}{(1 + \Psi^O + \Psi^S)^2}\right]. \end{aligned} \tag{1.22}$$

It is easy to see that cooperative incentive and free-riding incentive are related: a non-member i's free-riding incentive given a coalition S is the negative of its cooperative incentive, given a coalition $S \cup \{i\}$; a member j's cooperative incentive given a coalition S is the negative of its free-riding incentive, given a coalition $S \backslash \{j\}$.

1.4.2 Coalition Stability

An IEA is said to be stable provided it is both internally and the externally stable, or:

$$\Gamma_j^S(S) \geq 0, \forall j \in S, \tag{1.23}$$

$$\Gamma_i^O(S) \geq 0, \forall i \in O. \tag{1.24}$$

(1.23) is the internal stability condition, which requires a signatory of the IEA to be no worse off than outside of the IEA, and (1.24) is the external stability condition, which stipulates that any non-signatory should have a higher welfare outside of the coalition than if it joins the IEA. In summary, the coalition is stable if all members have non-negative *cooperative incentives* and all non-members have positive *free-riding incentives*.

Lemma 3. *If a member j's emission level is no lower than the level it would be at if it leaves the coalition, its cooperative incentive for the given coalition is positive.*

Proof. see A.1.5 □

With heterogeneous countries, it is not necessary that every coalition member reduces emissions. If a member could maintain at least the same emission level as when it was a non-member, its cooperative incentive is positive. In other words, this is a sufficient condition for $\Gamma_j^S > 0$. The cooperative incentive of a member from (1.19) can be decomposed into two parts: the change in the benefit of emissions and the change in climate change costs that include damages from emissions and adaptation costs. Since a country's benefit from emissions function increases in own emissions, if a member's emission level is not lower than if it leaves the coalition, the change of the benefit of emissions is non-negative. Moreover, since the world emissions level is always lower with a larger IEA, the member's climate change cost is lower when it chooses to stay in the IEA. Thus, any signatory that emits more in the coalition equilibrium than its non-cooperation level will certainly benefit from joining the IEA, as stated in the following result:

Lemma 4. *A member's equilibrium emissions level rises by forming the coalition iff* $\frac{\Phi_j}{\Phi^S} \geq \frac{1+\Psi}{1+\Psi^O+\Psi^S}$*, i.e. iff it is relatively vulnerable among all signatories.*

Proof. See A.1.6 □

In a world with heterogeneous countries, a signatory may be able to pollute more than its non-cooperative equilibrium level if it is relatively more vulnerable among signatories, and it will benefit by joining the IEA, as stated in Proposition 3.[23] However, if a signatory needs to curb its emissions when joining, its cooperative incentive depends on whether its reduced climate change cost is sufficient to compensate for the foregone benefit of reduced emissions. Relationships between emission changes and cooperative incentives are illustrated in Table 1.1.

Types	Emission Change	Cooperative Incentives
Strongly-cooperative: e.g., high $\frac{\Phi_j}{\Phi^S}$, low β_j	$e_j^S(S) \geq e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) > 0$
Weakly-cooperative: e.g., medium $\frac{\Phi_j}{\Phi^S}$, low β_j	$e_j^S(S) < e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) \geq 0$
Non-cooperative: e.g., low $\frac{\Phi_j}{\Phi^S}$	$e_j^S(S) < e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) < 0$

Table 1.1: Emission Changes and Cooperative Incentives[24]

[23] Goeschl & Perino (2017) obtain a comparable result in a setting without heterogeneous agents and adaptation, but where there is a hold-up problem due to rent-seeking by innovators.

[24] Exact conditions on Φ and β that define these types are found in A.1.7.

For any given coalition, there may exist three types of members based on their net vulnerability and change rate of the marginal abatement cost. *Strongly-cooperative* members are described in Lemmas 3 and 4. These countries are highly vulnerable to climate change compared to other members. A very vulnerable country maintains a low emission level in the non-cooperative equilibrium. After joining the IEA, its vulnerability is taken into account by all other members and the IEA as a whole reduces emissions. The global emissions level falls, although emissions reductions by the coalition are partly undermined by non-signatories. As a result, the highly vulnerable country can afford a higher emission level, and receives more benefit from emissions and less climate change damages. A *weakly-cooperative* member needs to reduce its emissions if it chooses to join the coalition, yet its total welfare rises: the reduced climate change cost by joining the coalition is enough to compensate for the foregone benefits of emissions. While with homogeneous countries, a stable coalition consists only of weakly-cooperative members, when countries are allowed to differ according to the various parameters of their benefit, damage and cost functions, a stable coalition may include a mix of strongly-cooperative and weakly-cooperative members. *Non-cooperative* countries can be less vulnerable than other members of the coalition. Such countries need to reduce a significant amount of emissions but benefit little from global emissions reduction, hence their welfare declines if they choose to join the coalition. Thus, non-cooperative countries cannot belong to a stable coalition since the free-riding on the coalition dominates.

1.4.3 Disparity in Vulnerability and Cooperative Incentives

Actual vulnerability to the impacts of climate change differs greatly across countries. In this section, we focus on the role of this disparity in vulnerability on the formation of an IEA. If the gap in net vulnerability is too large, less vulnerable countries are not likely to cooperate with highly vulnerable countries. Thus if countries differ much in net vulnerability, a large stable coalition is not likely to be formed.

Proposition 3. *In any given coalition, countries with a lower equilibrium level of ex-post or net vulnerability have lower cooperative incentives. If there exists at least one member j with relatively low net vulnerability, such that $\frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j} < \frac{\left[1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})\right]^2}{(1+\Psi^O+\Psi^S)^2}$, its cooperation incentive is negative and the coalition is not stable.*

Proof. See A.1.8 □

To better understand the role of heterogeneous vulnerability in countries' cooperative incentives and the structure of stable coalitions, suppose countries are symmetric on the benefit side (i.e. all have identical α and β parameter values). From (1.19), $\lim_{\Phi_j \to 0} \Gamma_j^S(S) < 0$, and $\lim_{\Phi_j \to \Phi^S} \Gamma_j^S(S) > 0$. Thus from continuity, there exists a threshold level $\Phi^* \in (0, \Phi^S)$ such that $\Gamma_j^S(S) = 0$. For countries with vulnerability greater than Φ^*, their cooperative incentives are positive. However, if a signatory's vulnerability is below Φ^*, its welfare rises if it leaves the IEA. The IEA is internally stable if and only if all signatories have vulnerability no less than the threshold level. Thus, from continuity, if the net vulnerability of members differs widely, less vulnerable countries are better off outside the coalition and an IEA cannot be formed.

This result implies that policies which assist vulnerable countries with adaptation technology can help reduce the gaps and foster a broader international cooperation on mitigation. Thus aid initiatives like the Green Climate Fund, which is meant to assist developing countries with adaptation may also be instrumental in forming a broad IEA on climate change mitigation.

1.5 Adaptation Technology Transfer

Free-riding on the mitigation efforts of members is the main problem preventing the formation of a large IEA (Yi, 1997; Finus, 2008). As a result, the size of a stable IEA in the literature is found to be typically small, or - as mentioned in the introduction - a high degree of cooperation can be achieved only when the gains of cooperation are small (Barrett, 1994, 1997; Pavlova & de Zeeuw, 2013). The literature on IEA formation has suggested several ways to extend cooperation (Carraro & Siniscalco, 1993; Hoel & Schneider, 1997; McGinty, 2007; Fuentes-Albero & Rubio, 2010), including side-payments, dispute settlement and monitoring mechanisms. However, as previously explained, the logistics of transfers and moral hazard issues make them problematic. Carraro & Siniscalco (1994) suggest that a cooperative technological innovation policy linked with an IEA can increase the size of the coalition, as the positive externality offsets the free-riding incentives, yet much of the previous research linking technological innovation and IEAs focuses on technology that reduces carbon emissions (Benchekroun & Chaudhuri, 2015; Goeschl & Perino, 2017). While a cooperative strategy on adaptation technology - such as a technology transfer - has been encouraged by the UNFCCC, its theoretical impact on the formation of an IEA has not been directly investigated so far.

So far, technological progress was assumed to occur exogenously in a country. In this section, we extend our previous framework by considering the possibility of technology transfer, to argue that technological progress in adaptation, provided as an excludable 'club good' to members of an IEA, can effectively reduce free-riding with respect to mitigation. In practice, if the IEA is accompanied by an R&D hub on adaptation technology, any innovation from the hub will be transferred to and adopted by members only. Moreover, if all members are required to contribute to financing of the R&D hub, free-riding with respect to adaptation technology within an IEA can be reduced.

Technological progress in adaptation in a country increases its effectiveness and/or reduce its cost of adaptation activities (θ_i rises and/or c_i falls), and hence reduces the net vulnerability to climate change Φ_i. New general adaptation technologies are transferred to members, and their vulnerability to climate change is reduced if the new adaptation technology can be adopted. Nevertheless, the new adaptation technologies invented somewhere else need to be adapted by each non-inventor country to its specific adaptation needs. In keeping with our previous full-heterogeneity approach, the extent to which a country can benefit from the general adaptation technology also varies across countries. Suppose the net vulnerability becomes $r_j\Phi_j$ for a member that has access to the technology, where $r_j \in [0, 1]$ is a country-specific coefficient measuring adoption costs. The higher the r_j is, the more difficult for country j to adopt the new technology, and the less it can benefit from the technology transfer. If a member j leaves the IEA, its access to the technology transfer arrangement ceases, and its net vulnerability reverts to Φ_j. Technological progress is assumed to be restricted to the members of the IEA. Thus for a non-member $i \in O$, its vulnerability remains Φ_i. The possibility of technology transfers has implications for IEA formation and stability.

Proposition 4. *If $\beta_i >> \Phi_i$, $\forall i \in N$, incentives to free ride on an IEA increase in the adoption cost; conversely, the more a country benefits from adaptation technology transfer, the lower its incentive to free ride on an IEA.*

Proof. See A.1.9 □

Incentives to free ride on an IEA can be reduced by a coalition which shares technological progress on adaptation among its members. A numerical example illustrating Proposition 4 is provided in Section 1.6. The opposite case to $\beta_i >> \Phi_i, \forall i \in N$ is trivial since it implies that the damage from emissions is much greater than the benefit from emissions and the net welfare can be negative for all countries.[25] Free riding on an international mitigation agreement can be reduced or even eliminated with the transfer of adaptation technology inside an IEA since the incentive to free ride is offset by the benefits stemming

[25] The exact condition for $\frac{\partial \Gamma_i^O}{\partial r_i} > 0$ can be found in A.1.9.

from the technology transfer. International cooperation on mitigation can be fostered by the formation of an R&D hub on adaptation technology which shares technological progress in adaptation. Moreover, if the R&D on adaptation technology is funded by all members of an IEA, free-riding with respect to adaptation inside an IEA can be reduced.

As a caveat, due to the constraints to this paper, this simple exercise does not offer a complete treatment of endogenous technology transfer, and is tantamount to treating it as exogenous. As already mentioned, we plan to endogenize technological progress, adoption and its diffusion in future research.

1.6 Simulation

Previous work on coalition theory and IEAs has shown that even when using identical agents, analytical solutions for the size of stable coalitions are typically not available in closed form with non-linear benefit and damage functions (Barrett, 1997; McGinty, 2007; Finus, 2008). Thus, simulation has been heavily relied upon to analyze the stability of coalitions. However, most studies focusing on formation and stability of an IEA assume arbitrary parameters (Barrett, 1997; McGinty, 2007; Pavlova & de Zeeuw, 2013). Botteon & Carraro (1997, 2001) analyze stability of an IEA using calibrated costs and benefits for five countries/regions. Botteon & Carraro (1997) focus on partial commitment and transfers, and find that with heterogeneous countries a transfer system can induce very high cooperation. Botteon & Carraro (2001) add carbon leakage (increasing marginal damages), and obtain an ambiguous impact of carbon leakage on the stability of an IEA. In terms of arriving at an analytical solution for the first stage of the membership game, we find ourselves in the same situation as the identical countries studies. Thus, we resort to a numerical simulation to explore the important question of the actual size of a stable coalition. Following Finus (2008)'s suggestion that simulations based on estimated parameters are particularly worth pursuing, we focus here on stability of a coalition and technology transfer using parameter estimated from climate change data.

1.6.1 Data and Estimation

The benefit of emissions function is estimated for each country using data on GDP and GHG emissions. GDP (current US dollars) is obtained from the World Bank (2014). The GHG emissions (kt of CO2 equivalent) are aggregated from CO_2, Methane emissions, Nitrous oxide emissions, and other greenhouse gas emissions (HFC, PFC and SF6), which are collected from the World Bank (2014).[26] Parameters α_i and β_i are estimated for each country using the above data from 1960 to 2010, as follows: [27]

$$GDP_{it} = \alpha_i e_{it} - \frac{\beta_i}{2} e_{it}^2.$$

To the best of our knowledge, there exists no comprehensive measure of cross-country cost and effectiveness of adaptation. Nevertheless, parameters in the damage function and cost of adaptation are integrated into net vulnerability, $\Phi_i \equiv v_i - \frac{\theta_i^2}{c_i}$, and Φ_i can be estimated using damages from climate change and the world's total GHG emissions from World Bank (2014). A caveat is that the estimated net vulnerability is likely to be below the actual vulnerability for two reasons: first, although the output side of adaptation is considered in estimating climate change costs, adaptation costs are not included due to lack of data; second, various indirect impacts of climate change can be large but are difficult to measure. Thus, our simulation exercise provides a conservative estimation of the role of vulnerability and the welfare gain potential of international cooperation on climate change. Using climate change costs in 2010 from DARA International (2012)[28] and the world's total GHG emissions from World Bank (2014), net vulnerability Φ_i is estimated for each country:

$$climate\_change\_cost_i = \Phi_i E^2.$$

Using the estimated α_i, β_i, and Φ_i and for computational simplicity, countries are clustered into 10 groups using the *k-means* method, whereby a representative country whose parameters are equal to the group mean is created for each group. Net vulnerability Φ_i is estimated using the actual global emission level; however this figure is much higher than the resulting emission level in the hypothetical 10 representative country world. To account for this discrepancy, Φ_i needs to be re-scaled using the climate change cost and the aggregate emission level of 10 representative countries. With these estimated parameters, α_i, β_i, and the re-scaled Φ_i, we simulate stable coalitions and the impact of adaptation technology transfers. Parameter values are reported in Table A.3 and they vary substantially across the 10 representative countries. For example, country 2 has a high emissions level and is the most vulnerable to climate change. It represents primarily a group of large developing countries, such as China and India. Country 3 represents developed countries that have high emissions levels and are less vulnerable to climate change, such as Canada.

[26] Once observations with negative α_i or βi are dropped, we are left with 143 countries. Summary statistics can be found in Table A.2.

[27] The α_i and β_i are estimated by ordinary least squares (OLS) with suppressed constant terms. Positive α_i and β_i are kept for the next step of clustering.

[28] For details, please visit http://daraint.org/climate-vulnerability-monitor/climate-vulnerability-monitor-2012/

1.6.2 Results

As shown in Table A.4, the largest stable coalition consists of four representative countries, $S = \{2, 4, 5, 6\}$, and it leads to 2.5% fall of global emissions. With a grand coalition, the world's emission level drops by 7.6% and the welfare rises by 0.8% compared to the non-cooperative equilibrium. Again, results should be viewed as conservative, in light of the fact that there are only 10 representative countries and their net vulnerability is under-estimated, as explained before.

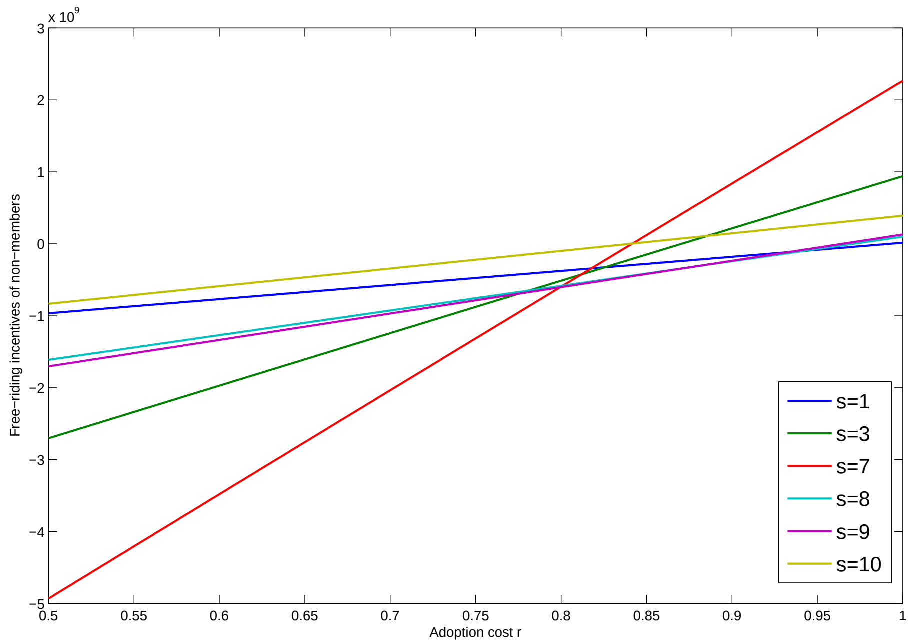

Figure 1.1: Free-riding Incentives and technological progress transfers: $\Gamma_i^O(r_i)$

As stated in Proposition 4, incentives to free ride on an IEA can be effectively reduced or even eliminated with a coalition where adaptation technology is shared among its members. Figure 1.1 illustrates that given the largest stable coalition S, non-members' free-riding incentives decrease as the adoption costs of new adaptation technology decrease. The set of non-members is $O = \{1, 3, 7, 8, 9, 10\}$. When $r_i = 1$, $\forall i \in O$ (the right end of Figure 1.1), the cost to adopt the new technology is too high, and countries do not benefit from the technology transfer if they choose to join the IEA. This case is equivalent to the model in Section 1.2, where technology transfers are not considered. Indeed, the free-riding incentives of these countries are positive, which is consistent with the external stability condition in Section 1.4. However, if $r_i < 1$, which indicates that non-member i can benefit from the technology transfer and reduce its vulnerability if it joins the IEA via adaptation technology transfers, country i's free-riding incentive decreases. Moreover, the lower the adoption cost index r_i, the more a non-member i can benefit from the within-coalition transfer, and the lower its free-riding incentive. Last, free-riding incentives of non-members can turn negative if the adoption cost is low enough. Therefore a non-member is willing to join the IEA if it benefits sufficiently from the transfer of adaptation technology as a signatory of the IEA.

1.7 Conclusion

This paper investigates the impact of adaptation technology on a country's incentive to participate in international GHG emissions-reducing agreements on climate change. We develop a framework where heterogeneity across countries is introduced with respect to the benefits and costs of both mitigation of emissions and adaptation to reduce the impacts of climate change. The paper focuses on the relationship between vulnerability-reducing adaptation technology and the formation of an IEA. We borrow and build on the general modeling framework introduced in Benchekroun et al. (2014), and we confirm the potential coalition-broadening role of technological progress in adaptation. In addition, we find that differences among countries in their net climate change vulnerability have important implications for cooperation. Exogenous technological progress in adaptation in highly vulnerable countries can foster an IEA on mitigation. If an IEA exists, advances in adaptation technology create a positive externality among members. Furthermore, the transfer of adaptation technology among members of an existing agreement can reduce free-riding with respect to mitigation and enlarge an IEA. Lastly, we simulate stable coalitions with parameters estimated from climate change data, and demonstrate how adaptation technology transfers reduce free-riding on the mitigation efforts of an IEA.

The global debates around the issue of cooperation on climate change are becoming increasingly polarized, often with developing and developed countries on opposite sides. While the former are generally stressing global participation in emission reduction pledges, the latter insist on adaptation funding for the poorer and more vulnerable countries. The primary focus of the COP21 in Paris in 2015 was to reach a treaty on mitigation, in which the responsibility of reducing GHG emissions is shared between developed and developing economies. Our results shed some light on these practical international cooperation issues. First, we show how disparity in terms of vulnerability between countries prevents the formation of a large IEA. Thus, policies directed at helping the poorer and most vulnerable countries protect themselves against climate-induced impacts (e.g. the Cancun Adaptation Fund or the Green Climate Fund) can bring the negotiating positions of the two groups closer together, fostering cooperation between vulnerable and less vulnerable countries.

Second, mitigation and adaptation should be considered jointly. Mitigation of GHG emissions is a global public good, and hence countries have an incentive to free ride rather than to participate in a costly emission-reducing agreement. However, this type of free-riding incentives can be reduced by the transfer of adaptation technology among the members of the agreement. Therefore, an international mitigation agreement can be negotiated jointly with an R&D hub on adaptation technology which shares new technology only to members. Moreover, the paper shows that progress in adaptation technology in a member country generates a positive externality for other members. Thus, if an R&D hub on adaptation is formed within an international mitigation agreement, the cooperation incentives are enhanced just as free riding on adaptation innovation is reduced. In practice, the UNFCCC established the Climate Technology Centre and Network (CTCN) after COP 16 in Cancun. The CTCN provides technical assistance at the request of member countries and promotes transfers of climate technologies. The emerging network has provided technology transfer on mitigation and adaptation to nearly 60 countries. Our results provides support for the importance of adaptation technology transfer between member countries as a crucial pillar of climate change cooperation. In future work we plan to more closely model the membership decision when technology adoption and transfers are endogenous to the model.

Chapter 2

Innovation as Adaptation to Natural Disasters

2.1 Introduction

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

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

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

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

The existing body of research on the impact of extreme weather and natural disasters focuses mainly on short-run and long-run economic growth.[2] There has been an increasing recognition of the fact that weather shocks and technological progress form an important channel of the climate-economy interface. Surprisingly, this link has been the subject of few studies. Crespo Cuaresma et al. (2008) examine how catastrophic risks affect technology transfer and capital updating, and find that the degree of catastrophic risk is negatively

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

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

related to knowledge spillovers between industrialized and developing countries. Rodima-Taylor et al. (2012) and Chhetri & Easterling (2010) conduct case studies showing that weather realizations can stimulate impact-reducing innovation in agriculture. Taking a cross-country view, a study by Miao & Popp (2014) is the first attempt to examine risk-mitigating innovations induced by natural disasters. For domestic patent applications, they find positive responses to a country's past natural disaster damage, and no response to other countries' disaster damage for droughts and earthquakes. Hence, risk-mitigating innovation responds only to local disaster events, which seems to confirm the old saying that "necessity is the mother of invention." However, their results are likely to be influenced by heterogeneity across countries (with respect to patent systems and overall innovation capacity), making it difficult to identify the mechanism and driving force of innovation aimed at reducing disaster impact. For instance, foreign innovators are less likely to respond to disasters in a country with poor patent protection (especially of foreign innovations) as their innovation may be appropriated easily, and hence this poor protection reduces the potential profitability of the research enterprise. In contrast, this study analyzes the response of innovation to national disasters at a subnational level, where crucial confounding factors affecting innovation (e.g., institutional quality and income) are significantly more homogeneous across sections. One would expect this approach to reveal a more accurate assessment of the interaction between disaster damages and the location of innovations.

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

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

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

This paper is structured as follows. Section 2.2 introduces the mechanism through which natural disasters spur innovation at a local and a national level. Section 2.3 presents the empirical model, followed by data description in Section 2.4. Section 2.5 discusses potential endogeneity of disaster damage, and reports estimation results. Innovation in response to regional disaster damage as a robustness check is explored in Section 2.6. Section 2.7 concludes the paper and discusses the policy implications of the main findings.

2.2 Natural Disasters and Innovation: a Framework for Analysis

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

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

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

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

Nonetheless, if a disaster type is highly concentrated in certain states, the national aggregated disaster is primarily determined by the disaster damage in those states. For example, earthquake events mostly happen in the west coast of the U.S., and the earthquake damage from those states, such as California and Oregon, makes up a large portion of the earthquake damage in the U.S. In this case, Hypothesis 1 would not be rejected even if the impact-reducing innovation is localized to those high-risk states. Therefore, in order to further unveil the geographical scope of impact-reducing innovations, national disaster damage is divided into disaster damage in a given state, and in the rest of the U.S. If disasters happening in one place stimulate innovations anywhere in the country, impact-reducing innovation in a state should respond to disaster damage from the rest of the country. This is stated in Hypothesis 2, which will be examined in Section 2.6.

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

Note that some disaster events strike two or more states. Moreover, geographic proximity leads neighboring states to share similar environmental characteristics. Therefore, it is possible that the response of impact-reducing patents is localized at a larger regional level. An extension of Hypothesis 2 at a regional level that groups a state and its neighboring states is examined in B.5.

2.3 Empirical Analysis

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

$$R_{jit} = f\left(D_{jit-1}, ..., D_{jit-n}, C_{it}, \eta_i\right), \tag{2.1}$$

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

The adaptive capacity, which represents the preparedness to respond to natural disasters, is unobserved. A line of empirical research explores characteristics that affect the capacity to cope with natural disasters in human systems. Income level is widely confirmed to have an influence on a region's capacity to adapt to natural disasters (Kahn, 2005; Toya & Skidmore, 2007; Mendelsohn et al., 2012).[3] Second, innovation capacity is an important

[3] Other factors such as institution quality, corruption and governance may also influence adaptive capacity in a country (Anbarci et al., 2005; Toya & Skidmore, 2007). However, heterogeneity of institution

factor in measuring the adaptive capacity (DARA International, 2012). Moreover, disaster impact-reducing innovations in a state is directly influenced by the state's innovation capacity. Thus, the overall innovation capacity is a crucial variable and is captured carefully from both the output and the input of the innovation process. The output of innovation in a state is measured by its total patent counts. The input side is measured by the higher education research and development (R&D) expenditure and R&D tax credit rate, which is shown to provide financial incentives to invest in R&D (Bloom et al., 2002; Wilson, 2009).

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

$$V_{jit} = f\left(D_{jit-1}, ..., D_{jit-n}, X_{it,t-1}, \eta_i\right). \tag{2.2}$$

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

As the dependent variable is a non-negative count measure with no upper bound, count data models which rely on the exponential mean function are adopted for estimation. The basic model given in Eq. (2.2) can be modified to test the two hypotheses formulated in

quality and governance within a country is much lower than that cross countries, which is one of the reasons for the state-level analysis in this paper.

Section 2.2. The estimating equation employed to test Hypothesis 1 is,

$$E\left[V_{jit}|D,X\right] = exp\left(\sum_{k=1}^{m}\beta_k D_{jt-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{2.3}$$

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

As discussed in Section 2.2, in order to further unveil the geographical scope of impact-reducing innovation, Hypothesis 2 is tested using the following equation. Impact-reducing innovations of disaster type j in state i in year t are modeled as a function of the damage from disaster type j in the rest of the U.S. ($D_{j,-it-1}, ..., D_{j,-it-k}$), controlling for state i's past damage from disaster type j ($D_{jit-1}, ..., D_{jit-k}$) and other variables $\boldsymbol{X_{it,t-1}}$:

$$E\left[V_{jit}|D,X\right] = exp\left(\sum_{k=1}^{m}\beta_k D_{jit-k} + \sum_{k=1}^{m}\gamma_k D_{j,-it-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right). \tag{2.4}$$

2.4 Data

2.4.1 Patent Data

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

First, patents aiming at reducing the impact of a particular type of disasters are identified for floods, droughts and earthquakes, respectively. In the patent literature, search criteria including both keywords and classes are the most common method to filter targeted patents. Miao & Popp (2014) use keywords and/or classes and subclasses to identify patents related to a type of disaster. However, their criteria are quite restrictive, which yield a very small subset of all patents aiming at reducing the impact of a certain type of disasters. Here I augmented their criteria by adding other related classes and subclasses containing disaster names and other keywords. For example, the search criteria for flood involves more than 20 keywords (e.g. "flood control" and "flood prevention") in seven classes (e.g. Class 405 "Hydraulic and earth engineering" and Class 52 "Static structures (e.g., buildings)"). According to such criteria, more expansive and yet accurate lists of patents for flood, droughts, and earthquakes are extracted. The search criteria generate 113 domestic patents pertaining to flood impact-reducing technologies, 69 patents for droughts, and 387 patents for earthquakes. A complete list of search criteria for floods, droughts and earthquakes related patents is given in B.1. To ensure robustness of results to the various search methods, different criteria are employed and the results can be found in B.2 in the Appendix.

With the identified patents, the next step is to match patents to states according to inventors' addresses. A main issue in this process is that co-inventorship exists in patents on disaster impact-reducing technology. Given that the dependent variable in this model measures innovative activities at the state level, all inventors should be considered instead of only the first inventor. Hence, one patent count is assigned to each inventor's residential state.[4] Nevertheless, for the case where a patent has multiple co-inventors from the same state, repeated counts of inventors to a state can potentially cause a biased measurement of innovative activities. To avoid this problem, only one patent count is assigned to the state if a patent has more than one inventor from the same state.[5] For example, if a patent has three inventors, two of whom reside in New York and one resides in Texas, one count is assigned to New York and one to Texas. Patent counts pertaining to floods, droughts, and earthquakes at the state level are given in Table B.3, and maps of those patents at the state level are plotted in Figure B.2, B.4, and B.6.

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

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

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

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

to the years from 1977-2005.

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

2.4.2 Disaster Damage Data

Disaster data is retrieved from the Spatial Hazard Event and Losses Database for the US (SHELDUS^{TM}) developed by the Hazards & Vulnerability and Research Institute at the University of South Carolina. SHELDUS^{TM} contains economic losses (property damages and crop damages), fatalities and injuries for 18 types of natural hazard events.[8] The impact of disasters, which is the key explanatory variable in the model, is measured as economic losses from disaster events. A map of economic losses at the state level is plotted for each type of disaster, as shown in Figure B.1, B.3, and B.5. Generally speaking, economic losses are more representative than fatalities and injuries in measuring damage from natural disasters. Many disaster events, especially for droughts and floods, cause few

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

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

fatalities in developed countries like the U.S. As for injuries, the number of total injuries cannot paint the full picture of disaster damage since the severity of injuries is difficult to rate and is usually not reported. In addition, economic losses from natural disasters represent the potential value of the impact-reducing technology market, which provides profit incentives for potential innovators.

Nevertheless, models with fatalities as main explanatory variables are also examined to explore the response of innovation to different measure of disaster impacts. The results are reported in B.4.

2.4.3 Instrumental Variables

The goal of this study is to identify the impact of natural disasters on innovations, however they both may be affected by unobserved time-varying elements, such as institution quality and overall technology level. For instance, efficiency of the local institution is associated with lower disaster damage and a higher level of innovation. In this case, the estimated effect on impact-reducing innovation pertaining to a type of disaster is negatively biased. To correct for this endogeneity, variables that contribute to explain disaster intensity are employed as instrumental variables (IVs), and the control function approach is applied in Section 2.5.2. Note that the impact of disaster damage is examined at both the national and the state level. Thus, disaster damage is aggregated at the national level and the state level, and two sets of IVs are calculated respectively. Instrumental variables used for flood, drought, and earthquake damage are summarized in Table 2.1.

Table 2.1: Summary of instrumental variables

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

As suggested by the climate-economy literature, the impact of natural disasters is mostly determined by the intensity of disasters. Hence, a number of variables measuring the physical intensity of floods, droughts and earthquakes are used as IVs for disaster damage. The IVs for flood and drought damages are constructed from the Palmer indices retrieved from the National Climatic Data Center (NCDC) of the National Oceanic and

Atmospheric Administration (NOAA).[9] The Palmer indices (e.g. the Palmer Z-index and the Palmer Drought Severity Index) are widely used in climatology and climate-economy studies to measure drought or wetness conditions across the U.S.

The Palmer Z-index measures monthly moisture conditions and abnormality in an area. Two instruments for flood damage are created based on the Palmer Z-index: the maximum Palmer Z-index in the given year in an area (i.e. a state or the U.S.), and the number of months with Palmer Z-Index greater than 2.5 in a given area.[10] Since flood damage is aggregated at the national level and the state level in Eq. (2.3) and (2.4), two sets of these IVs are calculated from national and state-level Palmer Indices respectively

IVs for drought damage are constructed from the Palmer Drought Severity Index (PDSI), which is calculated from precipitation, temperature, and soil moisture data and has been widely used to recognize abnormality of drought conditions in a region.[11] In a similar fashion to IVs for flood damage, the minimum value of the PDSI in the given year and area (i.e. a state or the U.S.) and the number of months with PDSI smaller than -3 are generated as IVs for drought damage in a given area.[12]

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

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

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

[11] There are other Palmer indices that also measure drought conditions. One advantage of using the PDSI is that it provides insulation from the dependent variable, i.e. innovations pertaining to droughts. The PDSI is more exogenous and is expect to affect the dependent variable only through drought damage since man-made changes (e.g., increased irrigation and new reservoirs) that contain new technologies are not considered in its calculation

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

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

2.4.4 Other Controls

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

Table 2.2 reports the summary statistics of main variables in the empirical analysis. After merging the various data sets, our sample has 1,479 observations of 50 states and the Washington D.C. in the U.S. A summary for patent counts and disaster damage by state can be found in B.3.

2.5 Empirical Discussion and Results

Since the dependent variable is the number of granted patents on impact-reducing technology (of floods, droughts, and earthquakes respectively), count data models are applied to estimate Eq. (2.3) and (2.4). A conditional Poisson distribution of the dependent variable has been the most common assumption in the count data literature, given the attractive properties of its maximum likelihood estimators (Cameron & Trivedi, 2013). The Poisson quasi-maximum likelihood estimator (Poisson QMLE) is also robust to distributional misspecification, i.e. when the outcome variable conditional on the explanatory variables does not have a Poisson distribution (e.g., equidispersion is not satisfied), provided the conditional mean is correctly specified. Moreover, the pooled Poisson QMLE does not require strict exogeneity of regressors ($E[u_t|D_s] = 0$, for $\forall s$) for consistency (Cameron & Trivedi, 2013; Wooldridge, 2010). In the empirical models, Eq. (2.3) and (2.4), innovations at time

Table 2.2: Descriptive statistics

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

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

t may reduce disaster damage in future years, implying that previous disaster damage is weakly exogenous to innovations ($E[u_t|D_s] = 0$, for $s \leq t$). In this case, the pool Poisson QMLE still provides consistent estimates. Therefore, to begin with, Eq. (2.3) and (2.4) are estimated by the pooled Poisson QMLE with robust standard errors clustered on state to account for serial correlation. Nevertheless, the Poisson distributional assumption of equidispersion is often rejected in the data. In the case of overdispersion, standard errors tend to be conservative and cause inflation of the t-stat in Poisson estimates. For comparison, negative binomial (NB) models are also estimated, and in general they provide similar results with the Poisson QMLE for floods and droughts.

However, a weakness of the pooled Poisson or NB model is that coefficient estimates are biased in the presence of heterogeneity across groups. In terms of natural disasters, there is a significant diversity of environmental profiles and disaster risks across states. For example, floods happen mostly in the south, while droughts are more concentrated in the western part of the U.S. Hence it is necessary to control for a state's intrinsic characteristics, which are crucial for disaster types and damage. The Poisson fixed effect (Poisson FE) with multiplicative fixed effects, which control for states' time-invariant characteristics, provides consistent estimates if strict exogeneity of regressors is assumed. Eq. (2.3) and (2.4) are estimated with the Poisson FE model with robust standard errors that fix serial correlation (Cameron & Trivedi, 2005). From the summary in Table 2.2, patents pertaining to floods and droughts have unconditional variances less than twice that of the unconditional means, and hence overdispersion is not likely to be a concern (Cameron & Trivedi, 2013). Although the variance of patents is much larger than the mean for earthquakes, the large variance is mostly attributed to heterogeneity across states, and overdispersion can be significantly reduced after controlling state fixed effects. In case that overdispersion still exhibits with the Poisson FE model, a conditional likelihood method for NB fixed effect (NB FE) proposed by Hausman et al. (1984) is applied for comparison.[14]

2.5.1 Results

The above four approaches are applied to Eq. (2.3) and (2.4) for floods, droughts and earthquakes. The response of innovation in a state to the national damage is reported in Tables 2.3, 2.4, and 2.5 for floods, droughts, and earthquakes, respectively. The individual coefficient of disaster damage lags is the short term (yearly) effect of an increase in disaster damage, while the cumulative effect, which is a linear combination of coefficients of all the disaster damage lags, estimates the long term change of innovation. Five-year distributed lags are selected for the reported models based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

Across floods, droughts, and earthquakes, the long term impacts of natural disasters are generally significant and provocative on patents pertaining to a type of disaster. The short term effect, however, is less consistent across time due to the nature of disaster events and the innovation process. The occurrence of natural disasters is inconsistent across years, for example, a significant disaster event in one year and several small disaster events in another year). The impact of a significant disaster can be much larger than that of several small events. Moreover, the innovation process is also less predictable, and patents, as an outcome of this process, may not be generated every year. Thus, it is expected that the individual yearly effect is not all positive and significant. Nevertheless, the long-term cumulative effect presents a more accurate impact of natural disasters.[15]

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

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

Table 2.3: Patent counts in response to national flood damage

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

Pseudo R^2 is 0.3224 with Poisson QMLE controlling for state fixed effects.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Patents aimed at reducing the impact of floods respond positively to past national flood damage. One billion dollars of flood damage in the U.S. can lead to a 35% increase in impact-reducing patents in a state in the next five years on average, with small variations across methods used in (1)-(4) in Table 2.3. The Louisiana Flooding in August in 2016, which caused a $10 billion loss, would spur flood impact-reducing patents across states by 350% in the next five years.

Compared to floods, there is a longer stimulating effect on impact-reducing innovations pertaining to droughts. Across all of the models presented in Table 2.4, there is evidence of a significant and positive short-term and long-term effect of drought damage on patents

Table 2.4: Patent counts in response to national drought damage

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

Pseudo R^2 is 0.3537 with Poisson QMLE controlling for state fixed effects.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

pertaining to droughts. In 2015, drought conditions plagued western states (e.g., California, Nevada and Oregon) for more than six months and caused $4.6 billion in losses. The size of the cumulative effect suggests that, at the state level, patents aimed at reducing the impact of droughts would increase by 790% on average in the next five years.

The results for earthquakes vary from methods (1) to (4) in Table 2.5. Compared to pooled Poisson and pooled NB, the results are very close for Poisson FE and NB FE: the cumulative effect and most yearly effects are positive and significant. This implies that a state's intrinsic characteristics (e.g. natural hazard profiles) are crucial in analyzing the impact of earthquake damages. Since earthquakes are geographically concentrated

Table 2.5: Patent counts in response to national earthquake damage

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

Pseudo R^2 is 0.6009 with Poisson QMLE controlling for state fixed effects.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

in several states where plates motion is active (e.g., California, Oregon, and South Carolina), the intrinsic characteristics of states, such as locations, should be controlled by state fixed effects. Thus, the estimates by pooled Poisson and pooled NB are less likely to be consistent.[16] The cumulative effects in (3) and (4) of Table 2.5 reveal that $1 billion losses from earthquakes in the U.S. would spur about 11-13% more patents on earthquake impact-reducing technology in a state in the next five years.

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

2.5.2 Endogeneous Disaster Damages

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

However, since the focus of this paper is intentionally sub-national, endogeneity of disaster damage should be inspected according to the level of analysis. As stated in Hypothesis 1, innovation in a state may respond to aggregate disaster damage at the national level. In this case, unobserved factors affecting disaster damage in the wider U.S., such as federal institution quality and technology level, are not likely to account for disparities in innovation across states. Additionally, as explained in Section 2.1, the federal government performs a minor role in disaster response and does not have any program explicitly supporting innovation pertaining to natural disasters. Thus, endogeneity of national disaster damage in Eq. (2.3) seems to be substantially reduced. Nevertheless, for the suspected endogeneity of disaster damage, instrumental variables (IVs) and the control function (CF) approach can be used to correct the potential endogeneity bias.

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

The application of the CF approach is quite straightforward: endogeneous regressors are regressed on all exogenous variables in the first stage (regression on the control function); in the second stage, first-stage residuals (instead of first-stage predictors) are included as

[17] Several moment-based methods have been developed for count data to deal with weakly exogeneity and endogeneity. However, one major drawback of generalized method of moments (GMM) estimators is computational complexity, and availability of estimates is subject to variation in the data and model complexity (e.g., convergent problem with estimators), which is the case in this study. Nonetheless, GMM IV methods are discussed in B.6

additional regressors. The CF approach has several advantages such as consistent estimates with nonlinear models and computational simplicity, though a stronger assumption of IVs is required.[18] As described in Section 2.4, variables that measure disaster intensity are employed as instrumental variables (IVs). The main identification assumption is that disaster intensity affect impact-reducing innovations only by being correlated with disaster damage. Also, disaster intensity cannot be correlated with other factors affecting patents pertaining to natural disasters.

The control function proposed for Eq. (2.3) is the residual of a regression of national disaster damage on the all exogenous variables:

$$D_{jt} = \boldsymbol{\theta_1} \boldsymbol{Z}_{jt} + \boldsymbol{\theta_2} \boldsymbol{X}_{it,t-1} + \eta_i + \omega_{jit}, \tag{2.5}$$

where Z_{jt} is the set of two IVs for national disaster damage of disaster type j, and ω_{jit} is the residual to be estimated. In the first stage, the reduced form Eq. (2.5) is estimated with an ordinary least squares regression to obtain the residual $\hat{\omega}_{jit}$. In the second stage, one-year lag of the residual, $\hat{\omega}_{jit-1}$, is included in the Poisson MLE regression of Eq. (2.3) with state fixed effect.

Although Eq. (2.3) consists of multiple distributed lags of disaster damage, including multiple control functions (i.e. $\hat{\omega}_{jit-1}, ..., \hat{\omega}_{jit-n}$) is redundant and lead biased estimates of disaster damage. The intuition is that one control function can account for the unobserved variables that affect both innovation and disaster damage.[19] $\hat{\omega}_{jit-1}$ is selected since it contains most information of all past shocks, and is the best control for the endogeneity of disaster damage. Shocks that affect disaster damage usually are not transient. For instance, a reform of the national disaster response system would have long term effect on disaster damages; innovations, such as reinforced concrete structure, have lasting effects on reducing disaster damage once being constructed or installed. Moreover, including multiple lags of residual is not recommended in the second stage due to multicollinearity (with each other and with lags of disaster damage).

Table 2.6 presents estimates using the CF approach for national aggregated disaster damage.[20] Compared to those in Table 2.3, 2.4, and 2.5, where national disaster damage is treated as an exogenous variable, the long-term cumulative effects are positive and similar in magnitude. These results confirm the previous finding that, for all three types

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

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

[20] The results of first stage regressions, given in Eq. (2.5), are reported in column 1 in Table B.4 and B.5.

Table 2.6: Patent counts in response to national disaster damage with the control function

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

Column 1 and 2 list results for 48 contiguous states since NCDC does not provide Palmer indices for Alaska, Hawaii and Washington D.C. Pseudo R^2 is 0.3254, 0.3497, and 0.6043 with Poisson QMLE controlling for state fixed effects for floods, droughts, and earthquakes. Standard errors are presented in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

of disasters, impact-reducing innovation in a state is stimulated by nationally aggregate disaster damage. In addition, the endogeneity seems to be minimal in the context of national disaster damage, especially for floods and droughts. One billion dollars in losses would spur 37% and 171% more impact-reducing innovations pertaining to floods and droughts respectively, and the results are similar to those without IVs in Table 2.3 and 2.4. Nevertheless, for earthquakes, the cumulative effect of damage is larger than those in columns (3) and (4) of Table 2.5, which verifies the conjecture that endogeneity of disaster damage leads to a negative bias of the coefficient. Earthquake damage of $1 billion would result in a 21% increase in innovations pertaining to earthquakes, while the number is 11-13% without IVs. A possible reason is that both earthquake events and impact-reducing innovations are concentrated in the high-risk area, e.g., California. The national earthquake damage is highly correlated with the disaster damage in the high-risk states, and hence is less exogenous to impact-reducing innovation, of which a substantial portion also locates in the high-risk states.

2.6 Robustness Checks

As discussed in Section 2.2, if a disaster type is highly concentrated in certain states, such as earthquakes in the U.S., the national aggregate disaster is primarily determined by the disaster damage in those states. In this case, impact-reducing innovation in a state seems to respond to national disaster damage even if the impact-reducing innovation is actually localized to the high-risk states. Therefore, Eq. (2.4) is estimated to further investigate the geographical scope of impact-reducing innovation-more specifically, whether impact-reducing innovation as a response to natural disasters is indeed nationwide.

The empirical strategy is the same with that in Section 2.5. The regression results of innovation on disaster damage at the state level are presented in Table 2.7, 2.8, and 2.9 for floods, droughts, and earthquakes. For floods, the cumulative effects of disaster damage from the rest of the U.S. are positive and significant, as shown in the first cumulative effective from column (1) to (4) of Table 2.7. This indicates that flood impact-reducing innovation in a state is positively affected by disaster damage from other states. Also, the estimates for droughts across different methods show similar consistency: the cumulative effects of disaster damage from other states are positive and significant. Therefore, for floods and drought, disaster damage does not necessarily spur patents in local areas. Rather, disaster damage can stimulate patents somewhere more distant in other states. Combining the results from model (2.3), where innovation is stimulated by the national disaster damage, the response of impact-reducing innovation seems to be national rather than localized to where floods and droughts occur.

The results for earthquakes vary from methods (1) to (4) in Table 2.9. As discussed in Section 2.5.1, states' intrinsic characteristics, such as location and earthquake hazard, are crucial in analyzing the impact of earthquake damages. Therefore, models with state fixed effects in (3) and (4) of Table 2.9 provide consistent estimates compared to pooled models in (1) and (2). Moreover, the variance of patents pertaining to earthquake impact-reducing technology is much larger than its mean. Although the large variance is mostly attributed to heterogeneity across states, overdispersion may still exhibit even if state fixed effects are controlled. In this case, NB FE is preferred to Poisson FE.

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

2.6.1 Endogenous Disaster Damage

The model in Eq. (2.4) examines whether impact-reducing innovation in a state responds to disaster damage in other states, controlling for the disaster damage in the given state. In this model, unobserved factors that affect innovation, such as efficiency and transparency of the local government, may also impact the disaster outcome in this region given that local governments share a major role in natural disaster management. In this case, disaster damage in a state may be endogenous, but the estimated effect on impact-reducing innovation is negatively biased, which is favourable to our findings.[21] Nevertheless, for the suspected endogeneity of disaster damage in Eq. (2.4), IVs and the CF approach can be used to correct the potential endogeneity bias.

In Eq. (2.4), disaster damage is disaggregated to a state level and the rest of the U.S. The results in Section 2.5.2 suggest endogeneity between national disaster damage and

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

innovation in a state is less of a concern. Thus, it is plausible that disaster damage from the rest of the U.S. tends to be exogenous to impact-reducing innovation in a given state. Still, state-level disaster damage appears to be endogenous to unobserved factors that also affect innovation in a state. Therefore, disaster damage from state i, D_{jit}, is assumed to be endogenous, and the control function for Eq. (2.4) is the residual from

$$D_{jit} = \boldsymbol{\theta_1} \boldsymbol{Z}_{jit} + \boldsymbol{\theta_2} \boldsymbol{X}_{it,t-1} + \eta_i + \omega_{jit}, \tag{2.6}$$

where Z_{jit} is the set of two IVs for state-level damage of disaster type j, and ω_{jit} is the residual to be estimated. To obtain the residual $\hat{\omega}_{jit}$, Eq. (2.6) is estimated using the ordinary least squares regression with state fixed effects in the first stage.[22] In the second stage, a one-year lag of the residual, $\hat{\omega}_{jit-1}$, is included in the Poisson regression of model (2.4) with state fixed effect.

The estimated effects with the CF approach are presented in Table 2.10. The first cumulative effects are positive and significant for all three types of disasters, and this suggests that innovation in a state is stimulated by disaster damage in the rest of the country. In other words, impact-reducing innovation is not localized to where disasters occur. The second cumulative effects presents the impact of local disaster damage on innovation in the next five years. The impact of local disaster damage on patents in a given state are all positive, but only significant in the case of earthquakes. In summary, for all three types of disasters, the response of innovation appears to be national, despite earthquake impact-reducing innovation tends to be more localized compared to innovation pertaining to floods and droughts.

2.7 Conclusion

Natural disasters cause significant casualties and damage worldwide every year. Moreover, climate change is expected to dramatically increase the frequency and intensity of natural disasters in the future. This paper presents a conceptual model where perceived risk theory and profit motive are combined to account for innovation activities induced by natural disasters. Using the U.S. patent data and natural disasters data from SHELDUS^{TM} for the years 1977-2005, the state-level empirical analysis on floods, droughts, and earthquakes reveals that impact-reducing innovation as a responds to natural disasters is not localized to where disasters occur, that is, disaster damage spurs innovation in both nearby and

[22] The results of first stage regressions, given in Eq. (2.6), are reported in column 2 of Table B.4 and B.5.

distant states. According to the empirical analysis, $1 billion losses from flood events in the U.S. is predicted to stimulate a 35% increase in flood impact-reducing innovation in a state in the next five years. For droughts and earthquakes, $1 billion losses is predicted to spur 173% and 20% more innovations respectively. Although disaster damage spurs innovation anywhere in the country, there is variation across disaster types: flood or drought damage in a state does not necessarily spur innovation in local areas, whereas in the case of earthquakes, there is a notable response of state-level innovation to local earthquake damage.

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

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

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

Table 2.7: Patent counts in response to flood damage at the state level

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

Pseudo R^2 is 0.3280 with Poisson QMLE controlling for state fixed effects.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.8: Patent counts in response to drought damage at the state level

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

Pseudo R^2 is 0.3623 with Poisson QMLE controlling for state fixed effects.
Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.9: Patent counts in response to earthquake damage at the state level

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

Pseudo R^2 is 0.4117 with pooled Poisson QMLE. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.10: Patent counts in response to disaster damage with the control function

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

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

Chapter 3

Water Innovation and Water Governance: Adaptive Responses to Regulatory Change and Extreme Weather Events

3.1 Introduction

Increased policy stringency is largely credited with vastly improved environmental outcomes in many industrialized economies starting with the second half of the twentieth century. In general, requiring ever higher standards on air, water and land pollutants works provided that existing production processes can - in a cost-effective way - be modified to have a reduced ecological footprint and/or new 'greener' technologies can be adopted. For environmental policy to be successful in a broad sense, it needs to lead to a cleaner environment based not on a reduced scale of economic activity, but rather following what is called in the literature a strong 'technique effect', i.e. the adoption of cleaner methods of production. Improved technical efficiency of production across the economy augments the policy-driven, allocative efficiency-enhancing effect of internalizing detrimental environmental externalities. Therefore, technological innovation aimed at reducing pollutants per unit of production needs to be developed in lockstep with the adoption of higher environmental standards.

This is particularly true when it comes to policies governing the industrial and residential use of water. From the lead contamination of municipal drinking water supply in

Flint, Michigan (2016) to the Deepwater Horizon oil spill in the Gulf of Mexico (2010), recent as well as more distant examples of accidents involving drinking water quality and water bodies pollution in the US abound, unfortunately. Due to their obvious importance for human health, these examples usually do deserve and attract a lot of attention. While many negative environmental outcomes can be attributed to 'natural' forces, others can be traced to 'man-made' failures of policy or insufficient regulation. This paper takes a closer look at the link between water policy and water-related technological innovation in the US. It focuses on the adoption and amendments of several critically important pieces of legislation driving water policy at the federal and state levels and it asks whether these acts spur a significant amount of related technological innovation.

To summarize our findings, the effects of water regulation on relevant innovation activity in the US is in general both statistically and economically significant. On *drinking water quality*, both amendments to the Safe Drinking Water Act and changes to the list of regulated contaminants are found to have a stimulating effect on patenting of related technologies. One newly added substance to the list of regulated chemicals leads on average to a 2% increase in relevant patents every year. On *water pollution*, federal legislation in the form of amendments to the Clean Water Act are found to induce a 10% increase in general water pollution reduction technologies and a 32% increase in the precise regulated pollutant-specific patents. Last, *water quantity* related technological patents respond positively to past economic damages due to water scarcity. For instance, a $1 bn. draught-induced damage is predicted on average to stimulate a 25% to a 46% increase in relevant patents in our sample. The stimulating effect of state water plans is also positive, but not a robust determinant of specific water-saving technological innovation, while appearing statistically significant for the more general group of water-related technologies.

While adopting rules such as maximum allowable levels for various contaminants in the drinking water supply, as well as maximum pollutant concentration of effluents from industrial and agricultural processes should in itself result in substantial environmental and public health gains, induced technological innovation can produce additional social benefits, by allowing the public and private sectors to achieve those targets with a lower net resource cost. Innovation can also yield broader social benefits via its positive external effects due to its public good nature (Arrow, 1962) and learning (Aghion & Jaravel, 2015), among others, as documented in a vast specialized literature. Hence, by reducing negative environmental externalities and increasing positive innovation-related externalities, there is great potential for environmental regulations to be welfare-enhancing, and consequently substantial payoffs from understanding the underlying mechanisms. In addition, quantifying the impact of water regulation on water-related technological innovation is important for its immediate policy relevance.

This paper draws on two bodies of literature in Economics: work on induced innovation and on the optimal water resource management. The induced innovation literature sheds light on the economic mechanism of endogenous technological change. Hicks (1932) observed that changes in relative prices of factors of production spur innovations that economize on the use of the relatively more expensive factor. In the 1960s, this idea of directed innovation due to variation in factor prices was formalized and further developed as 'induced innovation' by Ahmad (1966), Kamien & Schwartz (1968), and Binswanger (1974), among others. The theory of induced innovation would later be applied to environmental policy and technological improvement. If government regulations such as pollution permits affect the shadow price associated with a resource, firms are motivated to seek 'cleaner' methods of production (Downing & White, 1986; Milliman & Prince, 1989; Jaffe et al., 2003; Fischer et al., 2008).[1,2]

Accompanying this theoretical literature, a growing body of empirical research investigates the impact of public policy and induced technological change on a multitude of environmental issues.[3] A number of studies focus on energy-efficient technology, and suggest that government regulations affect firms' R&D expenditure and the direction of innovation (Jaffe & Palmer, 1997; Greening et al., 1997; Newell et al., 1999). Popp (2006) uses standards on nitrogen dioxide and sulphur dioxide across countries and finds that tightened standards stimulate more domestic innovations. In analyses of policy, Johnstone et al. (2010), Nesta et al. (2014) find renewable energy policy to have an influential impact on innovation of relevant technology within a country.

However, empirical evidence on the effect of public policy on water-related technological innovation remains scarce. A related stream of studies focus on a general category of 'environmental innovation,' which combines several different environmental domains, such as water, air, and soil. Brunnermeier & Cohen (2003) examine environmental innovations from US manufacturing industries and suggest that higher pollution abatement expenditures lead to more environmental innovation. Using cross-country patent data, Johnstone et al. (2012) and Ghisetti & Pontoni (2015) find environmental policy stringency to positively affect environmental innovation. Although these studies confirm that general 'environmental innovation' is affected by environmental regulations, very little has been uncovered on the specific topic of water regulations and water technology. A recent study by Conway et al. (2015) identifies water supply and demand technologies from a global patent dataset and analyzes recent trends in water technology. Their descriptive

[1] For a review of the theory, see Jaffe et al. (2002) and Popp et al. (2010).

[2] Induced innovation is also one of the channels suggested to explain the underlying mechanism behind the Porter Hypothesis.

[3] For recent reviews of such empirical studies, see Jaffe et al. (2002) and Vollebergh (2007).

analysis suggests that water scarcity, water regulations, together with the available research capacity play a substantial role in the emergence and development of water supply and demand technology. In this paper, we investigate the impact of changes in water policy in the U.S. on several different categories of water technology, using U.S. patent data and water legislations. To the best of our knowledge, this is the first paper that provides empirical evidence on how water technology innovation respond to adoption and changes in relevant public policy.

As mentioned above, this paper also draws on a vast body of literature on optimal water management. Much of this research discusses the efficiency and effectiveness of water governance structures and policy instruments in dealing with specific water issues (Convery, 2013). Although the vital role of water technology is widely discussed in water management and planning (Kundell, 2000; Wehn & Montalvo, 2014; Speight, 2015), there remains a paucity of evidence on how water regulations may contribute to shaping innovation on water technology. This issue is crucial in terms of designing water governance and improving social welfare, especially given the 'double externality' of environmental technology (Ghisetti & Pontoni, 2015), whereby new water technology both reduces negative externalities on water resources and generate positive externality to other sectors due to the spillover effect. In this paper, we investigate water policy as a determinant of water innovation in the U.S. and we provide empirical evidence that water innovation responds to water legislation and regulations. Our research sheds light on the potential impact of water policy on innovation, which should be taken into account in water management and planning.

3.2 Background

A brief review of the evolution over time of water management in the US can help build some understanding of the main kinds of water regulations and their potential impact on water technologies. This is particularly important since our empirical approach exploits the timing of water-related regulations as it related to changes in relevant technologies pertaining to either drinking water, wastewater pollution or water scarcity. Over the past century, water management in the US has seen substantial changes. In the nineteenth and early twentieth centuries, water resource development focused on finding ways to unlock the services provided by water as a primary resource. Both the private and the public sectors were mainly involved in projects such as canal and river improvements, flood control, water power, and irrigation. In 1802, as an outgrowth of the Gallatin Report of 1808, the US Army Corps of Engineers (USACE) was created as the first major water construction agency in the US and has since provided technical and engineering assistance to large-scale water projects across the US (Russell & Baumann, 2009).

Water resource management began to incorporate conservation and environmental protection objectives starting from the 1940s. The Senate Select Committee on Water Resources was established in 1959. Although the committee made no legislative actions, the studies and recommendations of this committee are viewed as 'a new era in water resources planning and development in the USA' (Warren Jr., 2009). The Water Resources Planning Act (WRPA) of 1965 was passed to encourage conservation and comprehensive planning of the nation's water and related resources. During the 1970s and 80s the federal government's major concern had shifted from water resources development to water quality and environmental protection. Several new pieces of legislation were established to address water quality concerns, such as the Water Pollution Control Act Amendments of 1972, the Safe Drinking Water Act (SDWA) of 1974, and the Clean Water Act (CWA) of 1977. A new regulatory agency, the US Environmental Protection Agency (EPA) was founded in 1970. While the EPA is largely considered to have been successful in governing federal environmental control programs, such as on water and air pollution, it also effectively separated the management of water quality from water quantity-related issues, such as managing water supply and demand.

Several different levels of government are presently involved in water resource governance in the US. While federal agencies such as USACE and the EPA play crucial roles in planning and developing water resources in the US, the majority of their focus has shifted to water quality and protection of water resources and restoration. Their role in other areas, such as water demand, supply and distribution, is currently limited. In contrast, state legislatures have dominant authority governing water issues related to construction, quantity, and distribution since the federal government has gradually abdicated that responsibility in the past half century. Most states have explicit water resource plans organized by water basins or resource types (e.g., surface water and groundwater), and many states have developed or are in the process of developing comprehensive state water plans, which address both water quality and water quantity issues within the state. Finally, local governments are mostly involved in drinking water supply, sewers and wastewater treatment.

3.2.1 Drinking Water Quality

Until the early 20th century, drinking water in the U.S. was managed by state and local governments. Federal regulation of drinking water did not begin until 1914, when the United States Public Health Service (PHS) standards were applied to drinking water provided by interstate carriers like ships, trains and buses. These standards were expanded and revised by the PHS three times from 1925-1962, and covered 28 substances in the 1962 version. At that time, the PHS standards were the most comprehensive drinking water standards and were followed by all 50 states as either regulations or guidelines for public drinking water quality (EPA, 1999). However, these standards were never mandated at the federal level (except for the said interstate carriers), and local laws of drinking water quality were often ignored or weakly enforced. Moreover, as a consequence of industrial and agricultural advances in the 20th century, many new man-made chemicals were released into the environment and entered drinking water supplies through various sources. The rising health concerns of drinking water in the US urged the federal government to conduct several studies on drinking water quality across the country. According to the survey findings of PHS (1970), more than half of the drinking water treatment facilities in the U.S. had major deficiencies in treatment processes. Another investigation by EPA (1972) found 36 chemicals in treated water from facilities along the lower Mississippi River. The increased prevalence of drinking water contamination and related health and environmental concerns eventually prompted Congress to take up and pass several legislative proposals, one of which was the Safe Drinking Water Act (SDWA) of 1974.

The objective of the SDWA is to ensure all public water supplies comply with the national standards. In 1974, the newly formed EPA was authorized by the SDWA to regulate public drinking water supplies by creating and revising national standards to control the levels of contaminants. However, new regulations on drinking water proceeded slowly: only 23 contaminants were regulated by the EPA during the decade after 1974. Congress was growing concerned with the slow progress under the EPA and unregulated water resources, and in 1986 the SDWA was significantly amended and reauthorized. In particular, the EPA was required to establish standards for 83 contaminants by 1989, and to add more contaminants periodically. The amendments also included monitoring of unregulated contaminants and suggesting 'best available technology' by the EPA.

The SDWA was subsequently amended several more times, and concurrently the role and responsibilities of the EPA on drinking water have been bolstered. In 1988, the Lead Contamination Control Act was passed as an amendment to the SDWA. In the early 1990s, issues such as lack of funding of local water treatment plants and missing public water quality information were brought to the public, and this raised the necessity of amending the SDWA again (Pontius, 2003). The 1996 amendments protected drinking water quality 'from the source to the tap' (EPA, 2004) and enhanced the existing drinking water regulatory framework in two notable ways (EPA, 1999). First, scientific evidence on adverse health effects and data analysis on contaminant occurrence and risk reduction were emphasized as inputs in the creation of contaminant standards. Second, both financial and technical assistance on water system infrastructure was required to be made available to states to ensure compliance with the national drinking water standards. Later, other laws and acts have changed parts of the SDWA. In 2005, the Energy Policy Act amended the SDWA with the purpose of excluding underground injection in hydraulic fracturing operation. The 2011 amendment of the SDWA set a more stringent definition of 'lead-free' for pipes, fittings and other plumbing products. The latest amendments in 2015, the Drinking Water Protection Act, addressed algal toxins in drinking water and required the EPA to assess and manage the risk.

Today drinking water quality in the U.S. is mainly regulated by the SDWA, under which the responsibility of ensuring safe drinking water is undertaken by the EPA, together with the states, tribes and other stakeholders. The EPA sets the National Primary Drinking Water Regulations (NPDWRs) based on scientific evidence of health risks and available technology. The NPDWRs regulate mandatory maximum contaminant levels (MCLs) for specific contaminants and mandates treatment techniques to remove contaminants. For example, the MCL of Arsenic is 0.01mg/L, while lead and copper are regulated by a treatment technique. Currently 94 contaminants are regulated by NPDWRs, which apply to all public water systems in the U.S. Furthermore, the EPA provides guidance and assistance to states, local water suppliers and the public, and oversees the implementation of national standards. The direct oversight of implementation may be assigned to states, if the states adopt standards at least as strict as the EPA standards. This status is called 'primacy,' which gives states 'the authority to implement SDWA within their jurisdictions' (EPA, 2004). Except for Wyoming and Washington D.C., all other states have received primacy status and have state agencies responsible for implementation of drinking water standards such as the NPDWRs.

3.2.2 Water Pollution

During the 1940s and 1950s, protection and improvement of environmental quality, especially water resource issues, began to capture the public interest. However, the federal government lacked both statute and executive branch capability to evaluate water resources and develop water usage or pollution control plans. In 1948, as the first major law to address water pollution, the Water Pollution Control Act was passed with the purpose of developing comprehensive pollution control plans for interstate rivers. Nonetheless, the legislation did not enforce pollution abatement procedures unless the involved state approved the action. A national comprehensive pollution control plan and enforceable water pollution regulations were still missing up until the early 1970s. After two years of debates and hearings, the Water Pollution Control Act Amendments of 1972 were enacted. The objective was to 'restore and maintain the chemical, physical, and biological integrity of the Nation's waters' (33 U.S.C. 1251). The 1972 Amendments departed from the original act in many remarkable ways, such as creating technology-based effluent standards and increasing funding for waste treatment works. Moreover, it introduced a permit system, the National Pollutant Discharge Elimination System (NPDES), for point sources of pollution.[4]

In 1977, the Water Pollution Control Act was amended again and became commonly known as the Clean Water Act (CWA). In the amendments, the act was revised to correct several shortcomings, such as a lack of financial and technical assistance to municipalities and weak enforcement. Nevertheless, non-point sources (e.g. agricultural fields and urban stormwater) remained exempt from the CWA. With concerns about water pollution sources growing, in 1987, the Congress amended the CWA through the Water Quality Act. The amendments focused on controlling non-point sources: states were required to prepare non-point source management plans and the exemption of NPDES permits was removed for both industrial and municipal stormwater. In addition, the Clean Water State Revolving Fund was created to improve wastewater treatment facilities and assist with cleanup programs.

3.2.3 Water Quantity

States have jurisdiction over the legal quantitative allocation of water resources, and have a long history of conducting water planning. During the 1960s and 1970s, the federal government was the main driving force behind water resource planning. The WRPA of 1965 supported federal and state comprehensive water planning. However, the National Water Commission (NWC), which was responsible for national water planning, was terminated by the Reagan administration in 1981. Since then, there has been no successful attempt at national water planning legislation, and state water planning is not mandated or financially supported by the federal government. Due to the importance of planning water resources, to date, all states have water resource plans with respect to one or more aspects of water management, such as flooding, water quality, and water project funding. For example, North Carolina has statewide resource plans, but maintains separate management plans for water supply and water quality. Yet, many states have developed statewide comprehensive water plans.[5]

State comprehensive water planning is a holistic approach that addresses many aspects

[4] Point sources includes industrial facilities, municipal governments and a few agricultural facilities.

[5] To date, 28 states have published their state water plans. For an overview of water plan structures and water planning legislation cross states, please see Dyckman (2016).

of water management, such as water quality, water quantity, and water resource protection. Although the structure and content may vary cross states, a comprehensive plan usually identifies pressures on water resources, articulates a statewide water vision, develops the framework of water management, and set forth state water policy and the role of related agencies. Therefore, comprehensive state water plans identify current and potential threats to water resources and are public signals of future policy directions.

3.3 Empirical Analysis

Previous studies of general environmental innovation include policy variables such as relative stringency and monitoring activities that measure the impact of environmental policy (Brunnermeier & Cohen, 2003; Johnstone et al., 2012). However, environmental laws and regulations usually are highly specific with respect to their object (e.g., drinking water, air, and wildlife), and general policy measurements do not precisely reflect the regulation status in a certain environmental area, such as drinking water. Therefore, in this paper we choose to focus separately on specific water issues like drinking water quality, water pollution, and water quantity, and we analyze the impact of direct regulatory changes in each of these domains on water-related technological innovation. The overarching mechanism we test for and measure in what follows is how the rate of water-related technological innovation in the US responds to specific changes in the regulatory framework governing each policy domain.

3.3.1 Drinking Water Quality

For our purposes, we measure drinking water innovation in a state using the number of patents specifically pertaining to drinking water technology, such as arsenic removal and disinfection treatment. In the U.S., drinking water quality is mainly regulated at the federal level by the SDWA. Therefore, any changes to the SDWA and related drinking water regulations (i.e. NPDWRs) potentially increase the demand for newer drinking water technology, thus stimulating innovation. Three dummy variables capture changes to the SDWA and the NPDWRs. First, a dummy variable indicates whether there are amendments to the SDWA in a given year. Two other dummies measure national drinking water standards: one indicates whether there is any new contaminant added to the list NPDWRs, and the other one indicates whether there is revision or deletion to the NPDWRs. Additionally, the total number of regulated pollutants under the NPDWRs is also adopted as a substitute for the above two variables as a robustness check.

Besides drinking water statutes and regulations, we need to control for other factors that potentially influence innovation on drinking water technology in a state. Innovation in a specific domain is likely to correlate with the general innovative capacity of the local economy, which is captured by total patent counts, per capita GDP, the level of higher education research and development (R&D) expenditure, and R&D tax credit rates. First, total patent counts in a state represents the output of overall innovation activities and is used in the literature as a measure of generally innovation propensity (Johnstone et al., 2012; Conway et al., 2015). Additionally, the number of total patents in a state controls for any potential changes in the patent system in a given year. Second, the income level and R&D expenditure are shown to also have a positive influence on a region's overall innovation capacity (Ulku, 2007; Johnstone et al., 2012). Income level is proxied in our analysis by state-level per capita GDP. There is a recognized data paucity on aggregated state-level R&D expenditure. Thus, we use higher education R&D expenditure and R&D tax credit rates, which provide financial incentives to invest in R&D (Bloom et al., 2002; Wilson, 2009), in order to measure the input side of innovation. Since innovation may require many months of work to bring an idea to fruition, one-year lagged higher education R&D expenditure and R&D tax credit rates are used in the empirical analysis, however the regression results are robust to adopting different time lags.

Innovation aimed at improving drinking water quality in state i in year t, Y_{it}, is represented as a function of the past variation in policy stringency (i.e. changes to the SDWA and the NPDWRs in previous years) $S_{t-1}, ..., S_{t-n}$ and controlling for other determinants, as follows:

$$E\left[Y_{it}|S, X\right] = exp\left(\sum_{k=1}^{m} \boldsymbol{\beta_k S_{t-k}} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{3.1}$$

where $X_{it,t-1}$ includes the following US state-level variables: total number of patents, per capita GDP, the higher education research and development (R&D) expenditures, and R&D tax credit rates. η_i is a state fixed effect that accounts for state specific factors such as water resource characteristics.

3.3.2 Water Pollution

Innovations aimed at reducing water pollution are measured as the number of patents pertaining to treatment of waste water, sewage, and sludge. Under the CWA - the primary law that regulates water pollution in the U.S. -, 126 toxic pollutants are analyzed and regulated by the EPA. In contrast to the NPDWRs of the SDWA, the pollutant list was revised only once since the 1977 amendments: three pollutants were removed from the list in 1981. In essence, the regulatory focus of water pollution can be characterized as more extensive than intensive, i.e. to expand regulations to exempted waste water sources rather than to enlarge the pollutants list. Indeed, previous amendments to the CWA have bolstered the authority of the EPA on those issues. As a result, the impact of any changes to the CWA is likely to have a long-term effect on technology. Therefore, we construct a cumulative variable of the amendments of the CWA: in a given year, it counts how many amendments have been enacted since the initial passing of the act in 1948.

Other factors may also determine innovation on water pollution in a state, such as the general propensity of innovation. Similarly with the analysis of drinking water innovations, the general propensity of innovation is controlled for by total patent counts, per capita GDP, the higher education research and development (R&D) expenditure, and R&D tax credit rate. Thus, innovation aimed at reducing water pollution, W_{it}, is represented as an exponential function of cumulative changes to the CWA, C_t, and controlling for other determinants $X_{it,t-1}$,

$$E\left[W_{it}|C, X\right] = exp\left(C_t + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right), \tag{3.2}$$

where η_i stands for the state-level fixed effects that account for the water resource profiles in state i.

3.3.3 Water Quantity

In contrast to the mostly federally-regulated water quality issues discussed above, the management of water quantity is mainly carried out at the state level in the US. Therefore, state water regulations are likely to affect innovations aimed at reducing water shortages, especially given that states have power over water rights (i.e., the quantitative legal allocation of water use). However, policies managing water demand and supply vary substantially across states, and hence are not directly comparable. As an alternative, we use comprehensive state water plans as a proxy measure for the state water quantity policy. A comprehensive state water plan usually includes a description of available water resources, potential pressure on these resources and water management goals, and it establishes a policy framework for water management. Thus, state comprehensive water plans are public signals of how actively the state government is engaged in water management and policy making. Currently, 28 states have developed comprehensive state water plans. We create a dummy variable to indicate whether a state publishes or updates its comprehensive water plan in a given year.[6]

Innovations aimed at mitigating water scarcity are also likely to be affected by past water shortage conditions such as droughts. One explanation is that water scarcity episodes raises the demand for adaptive technologies, which in turn motivates the private sector to invent newer and more effective technologies for mitigating this shortage. This hypothesis is based on the *theory of protection motivation*, according to which past experiences affect individuals' future risk perception, which has positive effects on self-protective behavior (Rogers, 1983; Maddux & Rogers, 1983). Several studies have applied this theory to document a positive association between climate change impacts such as increasing water scarcity and natural disasters damage and self-protective decisions (Cameron & Shah, 2015; Mishra & Suar, 2007; Greening & Dollinger, 1992). The empirical analysis by Li (2016) show that drought damages stimulate innovations aimed at reducing the impact of droughts. In summary, the demand for new technology increases due to protection motivation from water shortage, and the rising demand motivates more innovations targeted at reducing water shortage. Here we use economic losses from droughts to represent the past water shortage episodes since it represents the actual loss from water scarcity, as well as the potential market value of innovations aimed at mitigating water shortage.

Last, innovation activity aimed at mitigating water shortage in a state is again likely to be correlated with the overall innovation propensity in the state. Following the above Section 3.3.1 and 3.3.2: total patent counts, per capita GDP, higher education research and development (R&D) expenditures, and R&D tax credit rates are employed to control for general innovation capacity. Innovation aimed at reducing water shortage in state i in year t, V_{it}, are represented by a function of past state water plan dummies $P_{it-1}, ..., P_{it-n}$, past drought-related damages $D_{it-1}, ..., D_{it-n}$, other controls $X_{it,t-1}$ and state fixed effects η_i:

$$E\left[V_{it}|S, X\right] = exp\left(\sum_{k=1}^{m} \beta_k P_{it-k} + \sum_{k=1}^{m} \beta_k D_{t-k} + \boldsymbol{\mu X_{it,t-1}} + \eta_i\right). \tag{3.3}$$

3.4 Data

The dependent variables in our analysis are the total patents count of a certain type of water technology (e.g. conservation, purification, and wastewater treatment). These

[6] North Carolina maintains separate comprehensive planning for water quantity and quality. Although the state does not have a comprehensive water plan, its water supply plan takes an integrated approach to address water quantity issues. Therefore, besides the 28 states, North Carolina is treated as a state with comprehensive plan (on water quantity). The empirical results are robust to different treatments.

data were constructed through an extensive identification and matching process using the United States Patent and Trademark Office (USPTO) Patent Grant Bibliographic Text, which contains detailed patent information, including titles, abstracts, patent classes, and inventors' addresses of all granted patents since 1976. Note that another way to measure innovation is to count patent applications, both granted and declined. However, the patent application data are not quality-controlled and have crucial drawbacks, like the fact that publishing the application itself is at the applicant's latitude, hence published applications are only a subset of all actual patent applications.[7] Therefore, application data is not a precise measure of innovation activities at the state level. However, in order for us to capture the true timing effects of regulations, we use the date of application for all granted patents, rather than the date the patents were granted.

3.4.1 Drinking Water

Patents related to drinking water quality are identified through searching titles and abstracts using criteria based on classes and keywords. For example, the International Patent Classification (IPC) includes a designated class for water treatment: C02F 'Treatment Of Water, Waste Water, Sewage, Or Sludge,' which most patents on water technology belong to. Since the patent information in our database follows the United States Patent Classification (USPC), we refer to the USPC to IPC reverse concordance to search patents within the USPC classes corresponding to the IPC class C02F. [8] Note, however that restriction to certain patent classes may not be required if the search keywords are sufficiently specific. For example, one criterion includes searching for the phrase 'safe drinking water' in all patent classes. In our application, class C02F is combined with different such keyword searches in order to identify most related patents.

The keywords related to drinking water technology are compiled from EPA's publications on the SDWA (EPA, 1999, 2003, 2004), the NPDWRs, and drinking water technology indicated in state water plans. Depending on the types of keywords, the search criteria are divided into two categories: generic keywords and names of regulated contaminants. Search criteria with generic keywords (e.g., purification, filter, and disinfection) identify patents of drinking water treatment that is not specific to one contaminant.

On the other hand, patents on water technology aimed at eliminating specific contaminants are filtered through keywords derived from the names of the 97 contaminants listed

[7] For more details on this type of patent application data, see Li (2016).

[8] The concordance is provided by the USPTO at https://www.uspto.gov/web/patents/classification/international/ipc/ipc8/ipc_concordance/ipcsel.htm#a.

in the NPDWRs. For instance, patents aimed at removing Cadmium from the drinking water are identified by searching for the keywords, 'Cadmium' and 'drinking' and 'water' in all classes. This search criterion applies to most of the contaminants regulated by the NPDWR. However, some substances listed as contaminants in the NPDWRs may also found in patents related to non-water technologies. In order to eliminate irrelevant patents and have accurate search results, special criteria are designed for groups of contaminants such as radionuclides and microorganisms. Take radionuclides as an example: four contaminants (Alpha/photon emitters, Beta photon emitters, Radium 226 and 228, and Uranium) are listed in the NPDWRs as radionuclides. The search for patents aimed at reducing radionuclides in water is restricted to class C02F, and the keywords include the common names of these radionuclides and process words such as 'treatment' and 'filter.' Additionally, all keywords (except names of contaminants) are stemmed to the root component of each word (e.g., search filt* for 'filter' or 'filtration') in order to capture all words that have the same meaning.

Table 3.2 lists search criteria for patents aimed at improving drinking water quality, based on generic words and contaminant names. The empirical results in Section 3.5 are provided for two search criteria: Criterion 1 focuses on specific contaminants, and Criterion 2 includes both generic and contaminant keywords.[9]

After obtaining patents pertaining to improving drinking water quality, the next step is to assign patents to states according to inventors' addresses. In the case of co-inventorship, each inventor's information is collected and used to calculate patent counts at the state level. First, one count is assigned to the state in the inventor's address. Nonetheless, if a patent has several co-inventors from the same state, repeated counts of inventors to a state can potentially cause a biased measurement of innovative activities. Hence, only one patent count is assigned to the state if a patent has more than one inventor from the same state.[10] For example, if a patent has five inventors, two have addresses in New York and three have addresses in California, one count is assigned to New York and one to California.

The total count of patents pertaining to drinking water technology is computed according to the above rules for each state, and then sorted by application year. Compared to patent grant years, application years are not affected by patent processing time, which is about 28-35 months on average (USPTO 2014). Another problem caused by patent processing time is that the number of granted patents drop dramatically in the final years

[9] Nine search criteria with different keywords and combinations were designed and tested in the empirical analysis. In general, the regression results are robust to different search criteria.

[10] Another method of counting patents at the state level is to assign $1/n$ to each inventor's residence state, as done in Hovhannisyan & Keller (2015). The empirical results from different counting methods are very close.

Table 3.1: Patent search criteria for drinking water technology

Category	Keywords	Classes
Generic keywords		
Safe drinking water	Safe drinking water, drinking water standards, drinking water regulations	all
Treatment	+"drinking water" + treat*	C02F
Purification	+"drinking water" + purif*	C02F
filter	+"drinking water" + (filt* or microfilt*)	C02F
Disinfect/Sterilize	+"drinking water" +(disinfect* or steriliz*)	C02F
contaminants	+"drinking water" +(contamin* decontamin*) -animal	C02F
toxic	+"drinking water" +toxic*	C02F
desalination	+"drinking water" +desalin*	C02F
portable	+"drinking water" +portable	C02F
Contaminants		
General Criteria (apply to all contaminants except for the ones below)	name of a contaminant + "drinking" + "water" e.g. "Cadmium" + "drinking" + "water"	all
Special Criteria		
Radionuclides	+water +(photon "alpha particle" "beta particle" "alpha emitter" "beta emitter" radium uranium radionuclid*) +(treat* purif* filter* disinfect* steriliz* contamin* toxic* desalin*)	C02F
Water additive as disinfectant	+drinking +water +(Chlorine "chlorine dioxide" chlorite chloramines dichloramines) +(remov* reduc* eliminat* deliminat* treat* purif* filter* decontamin* contamin* toxic*)	C02F
Microorganism	+water +(Microorganism Cryptosporidium crypto "fecal coliform" "E. coli" "escherichia coli" Giardia Legionella "Total Coliforms" Viruses enteric) +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic*)	C02F
Microorganism: measurement	+drinking +water +(Turbidity "Heterotrophic plate count") +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic*)	C02F
Copper and lead	+drinking +water +copper +lead	C02F
Fluoride	+Fluoride +drinking +water +remov* -lead'	all
Nitrate and Nitrite	+(Nitrate nitrite) +drinking +water -sludge	all

of the sample period (many patents are still being processed and hence they are not published in the granted patent database). We take a conservative approach, which is also a prevalent method in the literature, and restrict the analysis to five years before the final year 2010.[11] Therefore, granted patent information is collected from USPTO for the years from 1977-2010, but the empirical analysis is limited to the period 1977-2005.

The SDWA and amendments

The SDWA was passed in 1974, and has been amended in 1986, 1988, 1996, 2005, 2011, and 2015. These amendments have significantly enhanced the authority of the SDWA in many aspects. For example, the 1988 amendment addressed lead and copper levels in drinking water, and the 1996 amendment required the EPA to strengthen the control of microbial contaminants and disinfectant byproducts. Thereby, as signals of more comprehensive and stringent regulations on drinking water, these amendments are likely to have stimulated the production of new drinking water technologies. A dummy variable is created to indicate whether there are amendments passed in a given year.

In addition to the amendments, the NPDWRs are national standards that are mandatory for all public drinking water systems. Any changes to the NPDWRs are likely to directly motivate innovations on drinking water technology. The NPDWRs are revised and expanded by the EPA from time to time, and the EPA maintains a timeline of any changes to the NPDWRs.[12] For each change, the record shows the year of Federal Register publication, name of the contaminants added, revised or deleted, and the total number of contaminants under regulation. Five variables are created from the information provided in the regulation timeline: whether there is a new regulation in a given year, number of contaminants newly regulated in a given year, whether there is revision or deletion in a given year, number of contaminants affected, and total number of contaminants under regulation. Table C.4 lists all changes to the SDWA and NPDWRs by year.

3.4.2 Water Pollution

Search criteria based on patent classes and keywords are designed to identify patents aiming to reduce pollutants in water effluents. We first use pollutant names and type of waste

[11] About 99% of granted patents were processed within five years in all patents pertaining to water quantity issues.

[12] The regulation timeline is published by the EPA at https://www.epa.gov/dwregdev/regulation-timeline-contaminants-regulated-under-safe-drinking-water-act

water regulated by the CWA as keywords to identify patents targetting specific pollutants from water or other waste discharge. This criterion is supposed to be the most stringent and relevant to the regulations under CWA. In addition, in order to eliminate irrelevant patents or include as many directly relevant patents as possible, special criteria are designed for some groups of contaminants such as the insecticide dichlorodiphenyltrichloroethane (DDT). Next, we also design a more general criterion including many generic keywords, e.g., waste water and sewage, to search for innovations on general waste water treatment technology. In addition, a third criterion is devised as a combination of criteria 1 and 2.

After obtaining patents aimed at reducing water pollution, the next step is to assign patents to states according to inventors' addresses. The rule of assigning patents is similar to the one applied to patents pertaining to drinking water quality in Section 3.4.1: one count is assigned to the state that is in the inventor's address, and no repeated counts to the same states if there are multiple inventors in a patent. Different counting rules are employed (e.g., assign $1/n$ to each inventor's residence state), and the results are quite close. The total count of patents pertaining to water pollution technology is computed according to the above rules for each state, and then sorted by application years. The empirical analysis is limited to the years from 1977-2005 (five years before the ending year 2010 in our dataset) due to the processing time of the USPTO.

The CWA and amendments

The first major law to address water pollution, the Water Pollution Control Act was passed in 1948. However, the act did not enforce pollution abatement procedures across states. In 1972, the act was bolstered through major changes, namely the Water Pollution Control Act Amendments of 1972. In 1977, the Water Pollution Control Act was amended again and now is commonly known as the CWA. Since 1948, the CWA has been amended 23 times. A cumulative variable counts the total number of the changes (including the act and its amendments) that have been enacted since the initial pass of the act in 1948.

3.4.3 Water Quantity

Here we focus on water technologies related to reducing water demand or expanding water supply. Most of the state comprehensive water plans address the importance of water technology: "DWR provides technical and financial assistance to [that] ... encourages water conservation, explores conjunctive use of groundwater and surface water, provides planning and advice on water recycling and desalination programs" (Summary of State Water Planning, California).

Table 3.2: Patent search criteria for waste water technology

Category	Keywords	Classes
Criterion 1	name of a pollutant +("waste water" "waste waters" "waste streams" wastewater* sewage stormwater* effluent)	C02F
Special Criteria		
Methylene chloride	"Methylene chloride" +("waste water" "waste waters" "waste streams" wastewater* sewage stormwater*)	C02F
Methyl chloride	"Methyl chloride" +("waste water" "waste waters" "waste streams" wastewater* sewage stormwater*)	C02F
4,4-DDT, 4,4-DDE, 4,4-DDD	+("4,4-DDT" "4,4-DDE" "4,4-DDD" Dichlorodiphenyl-trichloroethane dichlorodiphenyldichloroethylene dichlorodiphenyldichloroethane) +(contamin* "waste water" "waste waters" "waste streams" wastewater* sewage stormwater* effluent)	C02F
2,3,7,8-TCDD	+("2,3,7,8-TCDD") +("sludge" "waste water" "waste waters" "waste streams" wastewater* sewage stormwater* effluent)	C02F
Criterion 2	Criterion 1+ search criteria including generic keywords +("sludge" "waste water" "waste waters" "waste streams" wastewater* sewage stormwater*) +(remov* reduc* eliminat* deliminat* treat* purif* filter* disinfect* steriliz* decontamin* contamin* toxic* desalin*)	C02F

From state water plans, keywords of technology related to water quantity (e.g. reducing water demand or expanding sources of water supply) are collected to search for patents addressing water quantity issues. For example, the following terms (and their variations) are used as keywords to search for those patents:'water conservation,' 'saving water,' 'water desalination,' and 'water recycling.' A complete list of the search criteria is given in Table 3.3. The identified patents are then assigned to states according to the inventors' information, following the co-authorship attribution method described above.

The total count of patents pertaining to water quantity issues is thus computed and sorted by states and application years. Due to application processing delays at the USPTO, the analysis is again limited to five years before the ending year 2010 (the same procedure as described in Section 3.4.1). Thus, granted patent information is collected from USPTO for the years from 1977-2010, but the empirical analysis is confined to the period 1977-2005.

Table 3.3: Patent search criteria for technology on water supply and demand

Category	Keywords	Classes
Criterion 1		
Conservation	"water conservation", "water conserving", "conserve water", "conserves water", "conserving water", "conservation of water"	all
Saving water	"saving water" "save water" "saves water" "water saving"	all
Criterion 2		
Conservation	+water +conserv* -"energy conservation" -"conserving energy" -"conservation of energy"	all
Saving water	"saving water" "save water" "saves water" "water saving"	all
Desalination	+water +desalin*	all
Recycling	"water recycling" "water recycle" "recycled water"	all

State Water Plan

To date, 28 states have published state comprehensive water plans.Some states, such as California, Kansas and Missouri, have a more than 50-year comprehensive water planning history, while the comprehensive water planning efforts in other states, such as Colorado and Virginia, are more recent. A state water plan dummy indicates whether a state has a new version or a fully updated water plan in a given year. Nevertheless, when an old plan is updated, most states develop and publish a new version of the comprehensive water plan, whereas a few states, e.g., Montana, New Jersey and South Dakota, only update part of the old plan (e.g. for one section or for one region). Therefore, another dummy variable is created to capture a partly updated state water plan.

Drought Damage Data

Drought damage data is retrieved from the Spatial Hazard Event and Losses Database for the US (SHELDUS^{TM}) collected by the Hazards & Vulnerability Research Institute at the University of South Carolina. SHELDUS^{TM} contains economic losses (property damages and crop damages), fatalities and injuries for 18 types of natural hazard events.[13] Drought damage data is employed as a proxy for water scarcity, which is hypothesized to have a

[13] The 18 types are drought, earthquake, flooding, fog, hail, heat, hurricane/tropical storm, landslide, lightning, severe storm/thunder storm, tornado, tsunami/seiche, volcano, wildfire, wind, winter weather, avalanche, and coastal.

positive impact on innovations aimed at alleviating water shortage. In particular, we use economic losses from drought events, since economic losses are more representative than the much rarer fatalities or injuries in measuring drought-inflicted damages.

3.4.4 Other Controls

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

Table 3.4 reports the summary statistics of main variables in the empirical analysis. After merging the various data sets, our sample has 1,479 observations for 50 states and Washington D.C.

3.5 Empirical Results and Discussion

Since the dependent variable is the count of granted patents on water technology (i.e., drinking water quality, water pollution treatment, and water supply and demand), count data models are applied to estimate Eq. (3.1), (3.2) and (3.3).

The Poisson quasi-maximum likelihood estimator (Poisson QMLE) has been widely used in count data literature (Blume-Kohout, 2012; Cameron & Trivedi, 2013; Hovhannisyan & Keller, 2015), given its robustness to misspecification. First, the Poisson QMLE is robust to distributional misspecification, i.e. the dependent variable conditional on the

Table 3.4: Descriptive statistics

Variables	Mean	Max	Min	Variance
Drinking Water				
Patents (Criterion 1)	0.1244	0	4	0.1672
Patents (Criterion 2)	0.4226	0	8	0.8342
New_reg_SDWA	0.2414	0	1	0.1832
Rev_SDWA	0.2759	0	1	0.1999
Amend_SDWA	0.1379	0	1	0.1190
Water Pollution				
Patents (Criterion 1)	0.1690	0	5	0.2691
Patents (Criterion 2)	1.1427	0	17	3.5216
CumAmend_CWA	19.5862	12	22	9.2833
Water Quantity				
Patents (Criterion 1)	0.1941	0	12	0.4745
Patents (Criterion 2)	0.5321	0	17	1.5117
Update_SWP	0.0291	0	1	0.0282
Drought_dmg	1.1321	0	8.9593	3.0434
Other Controls				
PercapitaGDP	27.2351	9.7039	163.9650	263.0889
Total_patent	1.5205	0.0150	30.9330	7.4911
R&D_taxrate	-0.0117	-37.9457	0.2000	0.9755
Edu_R&Dexp	0.5148	0.0155	6.8104	0.5054

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

explanatory variables does not have a Poisson distribution, given the conditional mean is correctly specified. Moreover, the pooled Poisson QMLE does not require strict exogeneity of regressors ($E[u_t|D_s] = 0$, for $\forall s$) for consistency (Cameron & Trivedi, 2013; Wooldridge, 2010).

However, the weakness of pooled Poisson QMLE is that the estimates are biased in the presence of group heterogeneity. In the case of water innovations, environmental and governance profiles, which are likely to impact water innovation, vary significantly across states. First, water resource profiles (e.g., abundance and composition) are heterogenous across states in the U.S. For example, Alaska has ample water resources, which are largely in the form of ice, while California has chronic drought conditions. Hence, it is necessary to control for states' intrinsic water profiles. In addition, water governance at the state level, such as water management frameworks, legislation, and agencies, is highly diverse. Therefore, it is crucial to control for state-level variation of environmental and governance factors. We use the Poisson fixed effect (Poisson FE) with multiplicative fixed effects and robust standard errors to address the heterogeneity across states. The Poisson FE controls for time-invariant characteristics, and it provides consistent estimates even equidispersion is not satisfied. Nevertheless, in the case of overdispersion, standard errors tend to be conservative and cause inflation of the t-stat in Poisson estimates. Therefore, conditional likelihood method for negative binomial fixed effect (NB FE) proposed by Hausman et al. (1984) is applied for comparison.[14] Note that both methods provide similar results.

In addition, given the large number of zero counts in the dependent variables (e.g., 65% of zero counts in patents of drinking water technology), zero-inflated poisson (ZIP) and zero-inflated negative binomial (ZINB) models are employed to test the robustness,[15] and in general, the results are closed to the ones by Poisson FE and NB FE. Nonetheless, zero-inflated models are less preferred for three reasons. First, although the dependent variables have excessive zero counts, overdispersion is not likely to be a concern. From Table 3.4, the unconditional variances are about one to three times of the means. The conditional variances usually are substantially reduced since explanatory variables and group variation are controlled (Cameron & Trivedi, 2013). Moreover, the Vuong tests do not indicate that zero-inflated models fit better than the underlying Poisson or NB models. Last, the NB FE model performs much better than zero-inflated models based on Akaike information criterion (AIC) and Bayesian information criterion (BIC) statistics, which is consistent with the findings by Allison (2012). Therefore, results from Poisson FE and NB FE models are reported in the following sections.

3.5.1 Drinking Water Quality

Table 3.5 and 3.6 report the results on patents pertaining to drinking water technology for two different patent search criteria. The individual coefficient of the lags of regulatory variables gives the short term (yearly) effect of any changes of the act and its regulations, while the cumulative effect estimates the long-term effect. The number of lags (5-year lags) is selected based on the Akaike information criterion (AIC) and the Bayesian information criterion (BIC).

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

[15] Please see C.1 for density of the dependent variables and regression results.

Table 3.5: Patent counts (Criterion 1) in response to drinking water regulations

	SDWA dummies		Total number of contaminants	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
sdwa_reg_n			0.0216***	0.0207***
			(0.00437)	(0.00458)
L.sdwa_newreg	0.535	0.463		
	(0.382)	(0.317)		
L2.sdwa_newreg	0.291	0.277		
	(0.296)	(0.303)		
L3.sdwa_newreg	0.535	0.470		
	(0.333)	(0.359)		
L4.sdwa_newreg	0.582	0.627		
	(0.336)	(0.329)		
L5.sdwa_newreg	0.373	0.376		
	(0.445)	(0.442)		
Cumulative effect	2.315*	2.212*		
	(1.109)	(1.067)		
L.sdwa_revised	-0.441	-0.398		
	(0.333)	(0.317)		
L2.sdwa_revised	0.117	0.0730		
	(0.300)	(0.276)		
L3.sdwa_revised	0.198	0.154		
	(0.282)	(0.310)		
L4.sdwa_revised	0.344	0.289		
	(0.344)	(0.291)		
L5.sdwa_revised	0.243	0.185		
	(0.366)	(0.419)		
Cumulative effect	0.461	0.302		
	(0.839)	(0.798)		
L.sdwa_amend	0.280	0.400	0.154	0.254
	(0.328)	(0.344)	(0.317)	(0.302)
L2.sdwa_amend	0.627	0.603	0.492	0.499
	(0.428)	(0.378)	(0.284)	(0.256)
L3.sdwa_amend	0.399	0.322	0.180	0.138
	(0.339)	(0.367)	(0.204)	(0.243)
L4.sdwa_amend	0.339	0.437	0.151	0.218
	(0.270)	(0.283)	(0.261)	(0.219)
L5.sdwa_amend	0.211	0.294	0.181	0.237
	(0.291)	(0.316)	(0.237)	(0.222)
Cumulative effect	1.857*	2.055*	1.158	1.345*
	(0.753)	(0.929)	(0.635)	(0.644)
pcrealGDP	0.0588	0.0770*	0.0643	0.0772*
	(0.0355)	(0.0336)	(0.0364)	(0.0307)
patcount3	0.129*	0.124*	0.0970*	0.0979*
	(0.0627)	(0.0499)	(0.0487)	(0.0439)
L.rd_cr_st	0.271	0.115	0.129	0.0945
	(3.439)	(0.684)	(0.397)	(0.566)
L.t_edurdexpdf	-0.880	-0.816*	-0.691	-0.649*
	(0.452)	(0.360)	(0.393)	(0.329)
N	1479	1479	1479	1479

Pseudo R^2 is 0.2416 with Poisson QMLE controlling for state fixed effects in (1). Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6: Patent counts (Criterion 2) in response to drinking water regulations

	SDWA dummies		Total number of contaminants	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
sdwa_reg_n			0.0171***	0.0161***
			(0.00301)	(0.00250)
L.sdwa_newreg	0.647***	0.629***		
	(0.172)	(0.170)		
L2.sdwa_newreg	0.366*	0.360*		
	(0.143)	(0.167)		
L3.sdwa_newreg	0.294	0.342		
	(0.209)	(0.195)		
L4.sdwa_newreg	0.307	0.376*		
	(0.158)	(0.179)		
L5.sdwa_newreg	0.0112	0.000834		
	(0.252)	(0.244)		
Cumulative effect	1.625**	1.709**		
	(0.604)	(0.577)		
L.sdwa_revised	-0.557**	-0.607***		
	(0.180)	(0.176)		
L2.sdwa_revised	0.136	0.0953		
	(0.143)	(0.149)		
L3.sdwa_revised	0.318	0.292		
	(0.178)	(0.172)		
L4.sdwa_revised	0.379**	0.315*		
	(0.135)	(0.160)		
L5.sdwa_revised	0.316	0.307		
	(0.226)	(0.232)		
Cumulative effect	0.592	0.401		
	(0.497)	(0.452)		
L.sdwa_amend	0.379	0.407*	0.215	0.221
	(0.221)	(0.187)	(0.203)	(0.160)
L2.sdwa_amend	0.395	0.405*	0.383*	0.377**
	(0.247)	(0.201)	(0.174)	(0.141)
L3.sdwa_amend	0.0493	0.0357	0.0909	0.0856
	(0.216)	(0.200)	(0.0965)	(0.135)
L4.sdwa_amend	0.329**	0.358*	0.214	0.215
	(0.120)	(0.160)	(0.112)	(0.125)
L5.sdwa_amend	0.172	0.183	0.203	0.214
	(0.180)	(0.177)	(0.123)	(0.126)
Cumulative effect	1.325*	1.389**	1.105**	1.113**
	(0.565)	(0.507)	(0.406)	(0.352)
pcrealGDP	0.00716	0.0127	0.0136	0.0168
	(0.0301)	(0.0188)	(0.0316)	(0.0174)
patcount3	0.0689*	0.0665*	0.0381	0.0397
	(0.0312)	(0.0277)	(0.0230)	(0.0241)
L.rd_cr_st	0.121	0.117	0.0984	0.105
	(0.128)	(0.372)	(0.0953)	(0.379)
L.t_edurdexpdf	-0.433	-0.347	-0.244	-0.177
	(0.259)	(0.189)	(0.228)	(0.167)
N	1479	1479	1479	1479

Pseudo R^2 is 0.3132 with Poisson QMLE controlling for state fixed effects in (1). Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

The long-term effects (cumulative effects) of new regulations and amendments to the act are positive and significant across different model specification and patent search criteria. Nonetheless, the short-term effect (e.g., individual coefficient of lags of sdwa_newreg) is less consistent across time and different model specifications. A possible reason is that the innovation process is unpredictable, and patents as an outcome of this process may not be regularly generated every year. Moreover, including multiple lags of a variable results in substantial collinearity. Therefore, the individual coefficient of the regulatory variables (i.e. *sdwa_newreg, sdwa_revised*, and *sdwa_amend*) may not be properly estimated. However, according to Wooldridge (2009), the linear combination of the entire bundle of collinear variables is well-estimated. Hence, the individual short-term effect is not all positive and significant over time, whereas the long-term effect provides accurate estimation of the overall impact.

In general, if there are new contaminants added to the NPDWRs, patents on drinking water technology are substantially stimulated in the next five years (columns (1) and (2) in Table 3.5 and 3.6). Since *sdwa_newreg* is a dichotomous variable that measures whether there are any new contaminants added to the NPDWR in a given year, the marginal effect from its coefficient does not provide information for the impact of *one* newly regulated contaminant. Nonetheless, this impact can be calculated from regressions on total number of regulated contaminants (columns (3) and (4) in Table 3.5 and 3.6). The coefficients of total regulated contaminants are all positive and significant with different estimation methods and search criteria, which indicates that patents of drinking water technology are positively affected by the NPDWRs. On average, a newly regulated contaminant in the NPDWRs is predicted to stimulate the creation of related patents on drinking water technology by 1-2% in the given year.[16]

The SDWA amendments also lead to more patents pertaining to drinking water technology. For patents of technology aimed at removing specific contaminants (Criterion 1), amendments in a given year are predicted to result in 540% increase in the following five years (based on the coefficient 1.857 in Table 3.5). For patents pertaining to more general drinking water technology (Criteria 2), amendments in a given year would lead to 276% more of such patents in the following five years (based on the coefficient 1.325 in Table 3.6). It is expected that the impact of amendments is more substantial than the impact of a regulated contaminant. A likely reason is that drinking water quality is protected nationally by the federal law, and any change to the legislation is a clear signal of substantial improvements on drinking water governance across the country. Last, there is no evidence that revisions of the NPDWRs affect drinking water patents.

[16] The effect is based on the coefficents 0.0216 in Table 3.5 and 0.0161 in 3.6. All marginal effects are calculated using the transformation $e^{\beta} - 1$.

Note that, in general, the results are similar for patent search criteria 1 and 2. Nonetheless, the impact of the SDWA amendments on patents is not significant in all cases for patents searched by Criterion 1. Patents searched by the names of contaminants are innovations aimed at specific contaminants regulated by the NPDWRs. Thus, it is expected that this type of innovation responds significantly to any new regulations in the NPDWRs, but not strongly to the SDWA and its amendments.

3.5.2 Waste Water and Water Quality

Table 3.7: Patent counts in response to the CWA amendments

	Criterion 1		Criterion 2	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
cwa_amendcum	0.277**	0.278***	0.101**	0.100**
	(0.0882)	(0.0837)	(0.0356)	(0.0319)
pcrealGDP	0.0116	0.0109	0.00132	0.00233
	(0.0342)	(0.0337)	(0.0128)	(0.0120)
patcount3	0.00740	-0.000634	0.0461*	0.0461*
	(0.0298)	(0.0417)	(0.0199)	(0.0185)
L.rd_cr_st	0.111	0.107	0.0766	0.0801
	(0.0902)	(0.608)	(0.0403)	(0.153)
L.t_edurdexpdf	-0.161	-0.0493	-0.395**	-0.357**
	(0.229)	(0.304)	(0.142)	(0.133)
post_97	0.0129	0.0418	-0.133	-0.147
	(0.637)	(0.692)	(0.299)	(0.257)
year	-0.0799	-0.0847	0.00250	0.000219
	(0.0465)	(0.0488)	(0.0190)	(0.0180)
N	1479	1479	1479	1479

With Poisson QMLE controlling for state fixed effects, Pseudo R^2 is 0.3193 and 0.3911 for patents searched by Criterion 1 and 2, respectively. Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.7 reports the results of Eq. (3.2) for two patent search criteria on waste water treatment technology. Patents pertaining to wastewater treatment respond positively to changes of the CWA. On average, any amendments to the CWA in a given year are predicted to stimulate a 10% yearly increase in patents aimed at reducing water pollution (columns (3) and (4) in Table 3.7). Moreover, pollutant-specific patents respond more significantly: on average, amendments to the CWA would result in 32% more of such patents, as given in columns (1) and (2) in Table 3.7 (coefficient 0.277). In summary, legislations on water pollution lead to more innovations pertaining to pollution treatment technology.

3.5.3 Water Quantity

Table 3.8 reports the results of Eq. (3.3) for patents pertaining to water supply and demand. In general, the long-term effect of state water plans is positive and significant.[17]. Criterion 1 is based on water conservation technology, while Criterion 2 covers broader categories of water technology including water conservation, desalination and recycling. Compared to the results of Criterion 1, the impact of state water planning is more significant for Criterion 2, which covers broader water supply and demand technology. A likely explanation is that state comprehensive water plans address broader water pressures and tend to lead the overall development of water supply and demand technology. Take the coefficient in column (4) as an example (1.328), a new state water plan would spur 277% more patents on water supply and demand technology in the given state in the following five years.

In addition to water planning, national drought damages also positively affect patents pertaining to water supply and demand. According to the cumulative effects in Table 3.8, $1 billion drought damages are predicted to stimulate 25% to 46% more patents on water supply and demand technology in the next five years. Water scarcity episodes, measured by drought damage, are likely to motivate private sectors to invest and innovate technologies that reduce water demand and expand water supply. The results also confirm and extend the findings by Li (2016): drought damages spur related adaptation technologies.

3.6 Conclusion

Growing population and economic activities are placing increasing pressure on the water resources in the U.S. Water planning, water legislation and specific regulations are adopted to address water quality and quantity issues. These water governance practices have resulted in substantial improvements of environmental quality and public health. Additionally, more stringent water policy also induces the creation of new technology aimed at reducing water pollution or water shortage in a more efficient way. In this paper, we focus on water governance of three water issues: drinking water quality, water pollution,

[17] The exception is the cumulative effect of water plans given in column (2). Nonetheless, it is marginally significant at 10%)

Table 3.8: Patent counts in response to water planning and water scarcity

	Criterion 1		Criterion 2	
	(1) Poisson FE	(2) NB FE	(3) Poisson FE	(4) NB FE
L.waterplannew	0.139	0.0759	0.101	0.0952
	(0.343)	(0.319)	(0.139)	(0.174)
L2.waterplannew	0.123	0.0811	0.174	0.130
	(0.240)	(0.346)	(0.174)	(0.200)
L3.waterplannew	0.706^{*}	0.578	0.441^{*}	0.358
	(0.308)	(0.311)	(0.210)	(0.207)
L4.waterplannew	0.333^{*}	0.271	0.346	0.246
	(0.166)	(0.317)	(0.222)	(0.193)
L5.waterplannew	0.393	0.394	0.451^{*}	0.498^{*}
	(0.227)	(0.305)	(0.190)	(0.212)
Cumulative effect	1.694^{*}	1.493	1.512^{**}	1.328^{**}
	(0.768)	(0.987)	(0.554)	(0.585)
L.tdmg_c	0.0734	0.0608	0.0452	0.0395
	(0.0426)	(0.0353)	(0.0277)	(0.0219)
L2.tdmg_c	0.0993^{*}	0.0800^{*}	0.0721^{**}	0.0668^{***}
	(0.0394)	(0.0361)	(0.0221)	(0.0192)
L3.tdmg_c	0.105^{***}	0.0981^{**}	0.0671^{***}	0.0623^{**}
	(0.0286)	(0.0308)	(0.0188)	(0.0199)
L4.tdmg_c	0.0520	0.0497	0.0197	0.0155
	(0.0270)	(0.0350)	(0.0193)	(0.0208)
L5.tdmg_c	0.0486	0.0536	0.0353	0.0365
	(0.0344)	(0.0335)	(0.0220)	(0.0223)
Cumulative effect	0.379^{***}	0.342^{***}	0.239^{***}	0.220^{***}
	(0.113)	(0.094)	(0.0706)	(0.0552)
pcrealGDP	-0.00754	-0.00784	0.0240	0.0250^{***}
	(0.0346)	(0.0306)	(0.0130)	(0.00701)
patcount3	-0.0146	0.00380	-0.00417	0.00647
	(0.0443)	(0.0407)	(0.0288)	(0.0254)
L.rd_cr_st	3.480	3.148	3.346	3.038
	(2.235)	(2.400)	(2.135)	(1.748)
L.t_edurdexpdf	-0.0918	-0.158	-0.261	-0.321^{*}
	(0.312)	(0.288)	(0.200)	(0.157)
post_97	-0.369	-0.319	-0.615	-0.600^{**}
	(0.801)	(0.735)	(0.328)	(0.214)
N	1479	1479	1479	1479

With Poisson QMLE controlling for state fixed effects, Pseudo R^2 is 0.3750 and 0.3540 for patents searched by Criterion 1 and 2, respectively. Standard errors are clustered at the state level. Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

and water quantity. Starting from a comprehensive review of water governance history in the U.S., we first identify the major legislation and governance bodies pertaining to different water issues. Using data on water legislation and comprehensive water plans, the state-level empirical analysis reveals that water regulations and water plans have a stimulating effect on water-related innovation. For technology aimed at improving drinking water quality, innovations respond positively to new regulations under NPDWR and also to SDWA amendments. One newly regulated contaminant would lead to a 2% increase in relevant patents every year. Regarding water pollution issues, the CWA amendments lead to more innovations on waste water treatment technology. Our result shows that the amendments to the CWA would spur a 32% increase in patents targeting regulated pollutants. Last, innovation on water supply or demand technology is stimulated by state water planning and water scarcity measured by drought damage. General water supply or demand technology would increase by 277% in five years as a result of current state water planning and by 25% as a result of $1 billion drought damages.

Our research contributes to the large body of literature on induced innovation by providing first empirical evidence on innovation induced by water regulations. Moreover, our results have immediate policy implications on water management and policy design. Water regulations not only reduce negative environmental externalities but also induce water-related innovation that generates positive innovation-related externalities. Therefore, there is great potential for water regulations to be welfare-enhancing. Our empirical evidence contributes to quantifying the impact of water regulation on water-related technological innovation and hence to cost-benefit analysis of policy adoption.

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APPENDICES

Appendix A

The Appendix for Chapter 1

A.1 Proofs and Tables

A.1.1 Proof of Proposition 1

Proof. Suppose that a non-member country $i \in O$ experiences a technological progress in adaptation (i.e. adaptation measures become more effective and cost less: θ_i rises and/or c_i falls).

$$\frac{de_i^O}{d\Phi_i} = -\frac{1 + \Psi^O + \Psi^S - \Psi_i}{\beta_i \left(1 + \Psi^O + \Psi^S\right)^2} \overline{E} < 0.$$

All other countries respond in the opposite way:

$$\begin{aligned}
\frac{de_k^O}{d\Phi_i} &= \frac{\Psi_k}{\beta_i \left(1 + \Psi^O + \Psi^S\right)^2} \overline{E} < 0, k \neq i \in O, \\
\frac{de_j^S}{d\Phi_i} &= \frac{\Psi_j^S}{\beta_i \left(1 + \Psi^O + \Psi^S\right)^2} \overline{E} > 0, j \in S, \\
\frac{dE^N}{d\Phi_i} &= -\frac{1}{\beta_i \left(1 + \Psi^O + \Psi^S\right)^2} \overline{E} < 0.
\end{aligned}$$

The adaptation level is given by (1.16). The change in the equilibrium adaptation level of country i in the effectiveness and/or cost of adaptation are given by:

$$\begin{aligned}
\frac{da_i^O}{d\theta_i} &= \frac{\partial a_i}{\partial \theta_i} + \frac{\partial a_i}{\partial E^N}\frac{dE^N}{d\Phi_i}\frac{d\Phi_i}{d\theta_i} = \frac{E^N}{c_i}\left[1 + \frac{\theta_i^2}{c_i}\frac{2}{\beta_i\left(1+\Psi^O+\Psi^S\right)^2}\right] > 0, \\
\frac{da_i^O}{dc_i} &= \frac{\partial a_i}{\partial c_i} + \frac{\partial a_i}{\partial E^N}\frac{dE^N}{d\Phi_i}\frac{d\Phi_i}{dc_i} = \frac{\theta_i^2}{c_i}E^N\left[\frac{\theta_i^2}{c_i}\frac{1}{\beta_i\left(1+\Psi^O+\Psi^S\right)^2} - 1\right] \\
&< \frac{\theta_i^2}{c_i}E^N\left[\frac{\Psi_i}{\beta_i\left(1+\Psi^O+\Psi^S\right)^2} - 1\right] < 0.
\end{aligned}$$

Since technological progress in adaptation is associated with positive change of θ_i and negative change of c_i, adaptation level of country i increases.

Adaptation levels of other countries $k \neq i \in N$ increase as well,

$$\begin{aligned}
\frac{da_k}{d\theta_i} &= \frac{\partial a_k}{\partial E^N}\frac{dE^N}{d\Phi_i}\frac{d\Phi_i}{d\theta_i} > 0, \\
\frac{da_k}{dc_i} &= \frac{\partial a_k}{\partial E^N}\frac{dE^N}{d\Phi_i}\frac{d\Phi_i}{dc_i} < 0.
\end{aligned}$$

Suppose a member country j experiences technological progress in adaptation. Country j and all other members can now afford higher emission levels:

$$\begin{aligned}
\frac{de_j^S}{d\Phi_j} &= -\frac{1+\Psi^O}{\beta_j\left(1+\Psi^O+\Psi^S\right)^2}\overline{E} < 0, \\
\frac{de_k^S}{d\Phi_j} &= -\frac{1+\Psi^O}{\beta_k\left(1+\Psi^O+\Psi^S\right)^2}\overline{E} < 0, k \neq j \in S.
\end{aligned}$$

Non-member countries respond in an opposite fashion compared to members, by decreasing their equilibrium emissions:

$$\frac{de_i^O}{d\Phi_j} = \frac{\Psi_i \sum\limits_{j\in S}\frac{1}{\beta_j}}{\left(1+\Psi^O+\Psi^S\right)^2}\overline{E} > 0, i \in O.$$

World emissions level changes in the same direction as for member country j:

$$\frac{dE^N}{d\Phi_j} = -\frac{\sum\limits_{j\in S}\frac{1}{\beta_j}}{\left(1+\Psi^O+\Psi^S\right)^2}\overline{E} < 0.$$

The change of adaptation level of country j with the effectiveness and/or cost of adaptation are:

$$\begin{aligned}
\frac{da_j^S}{d\theta_j} &= \frac{\partial a_j^S}{\partial \theta_j} + \frac{\partial a_j^S}{\partial E^N}\frac{dE^N}{d\Phi_j}\frac{d\Phi_j}{d\theta_j} = \frac{E^N}{c_j}\left[1 + \frac{\theta_j^2}{c_j}\frac{2\sum_{j\in S}\frac{1}{\beta_j}}{\left(1+\Psi^O+\Psi^S\right)^2}\right] > 0, \\
\frac{da_j^S}{dc_j} &= \frac{\partial a_j^S}{\partial c_j} + \frac{\partial a_j^S}{\partial E^N}\frac{dE^N}{d\Phi_j}\frac{d\Phi_j}{dc_j} = \frac{\theta_j^2}{c_j}E^N\left[\frac{\theta_j^2}{c_j}\frac{\sum_{j\in S}\frac{1}{\beta_j}}{\left(1+\Psi^O+\Psi^S\right)^2} - 1\right] \\
&< \frac{\theta_j^2}{c_j}E^N\left[\frac{\Psi^S}{\left(1+\Psi^O+\Psi^S\right)^2} - 1\right] < 0.
\end{aligned}$$

Adaptation levels of other countries $k \neq j \in N$ increase as well,

$$\begin{aligned}
\frac{da_k}{d\theta_j} &= \frac{\partial a_k}{\partial E^N}\frac{dE^N}{d\Phi_j}\frac{d\Phi_j}{d\theta_j} > 0, \\
\frac{da_k}{dc_j} &= \frac{\partial a_k}{\partial E^N}\frac{dE^N}{d\Phi_j}\frac{d\Phi_j}{dc_j} < 0.
\end{aligned}$$

□

A.1.2 Proof of Proposition 2

Proof. The welfare of a country i is given by,

$$w\left(e_i, a_i, E\right) = e_i\left(\alpha_i - \beta_i\frac{e_i}{2}\right) - \frac{1}{2}\Phi_i\left(E^N\right)^2.$$

For a non-member country $i \in O$, the welfare increases if its own vulnerability decreases:

$$\begin{aligned}
\frac{dw(e_i^O)}{d\Phi_i} &= \beta_i\left(\bar{e}_i - e_i\right)\frac{de_i^O}{d\Phi_i} - \Phi_i\frac{dE^N}{d\Phi_i}E^N - \frac{1}{2}\left(E^N\right)^2 \\
&= \left[\frac{\Psi_i\left(\Psi_i - \Psi^O - \Psi^S\right)}{1+\Psi^O+\Psi^S} - \frac{1}{2}\right]\left(E^N\right)^2 < 0.
\end{aligned}$$

For other non-member countries $k \neq i \in O$, their welfare drops:

$$\begin{aligned}
\frac{dw(e_k^O)}{d\Phi_i} &= \beta_k\left(\bar{e_k}-e_k\right)\frac{de_k^O}{d\Phi_i}-\Phi_k\frac{dE^N}{d\Phi_i}E^N \\
&= \beta_k\Psi_k E^N\frac{\Psi_k}{\beta_i\left(1+\Psi^O+\Psi^S\right)}E^N+\frac{\Phi_k}{\beta_i\left(1+\Psi^O+\Psi^S\right)}\left(E^N\right)^2 \\
&= \frac{\Psi_k}{\beta_i}\frac{1+\Psi_k}{1+\Psi^O+\Psi^S}\left(E^N\right)^2>0.
\end{aligned}$$

The welfare of all member countries $j \in S$ decreases as well:

$$\begin{aligned}
\frac{dw(e_j^S)}{d\Phi_i} &= \beta_j\left(\bar{e_j}-e_j\right)\frac{de_j^S}{d\Phi_i}-\Phi_j\frac{dE^N}{d\Phi_i}E^N \\
&= \beta_j\Psi_j^S E^N\frac{\Psi_j^S}{\beta_i\left(1+\Psi^O+\Psi^S\right)}E^N+\frac{\Phi_j}{\beta_i\left(1+\Psi^O+\Psi^S\right)}\left(E^N\right)^2 \\
&= \frac{\Phi^S\Psi_j^S+\Phi_j}{\beta_i\left(1+\Psi^O+\Psi^S\right)}\left(E^N\right)^2>0.
\end{aligned}$$

If a member country $j \in S$ experiences technological progress in adaptation, its welfare change depends on its parameters relative to the coalition's.

$$\begin{aligned}
\frac{dw(e_j^S)}{d\Phi_j} &= \beta_j\left(\bar{e_j}-e_j\right)\frac{de_j^S}{d\Phi_j}-\Phi_j\frac{dE^N}{d\Phi_j}E^N-\frac{1}{2}\left(E^N\right)^2 \\
&= -\beta_j\Psi_j^S E^N\frac{1+\Psi^O}{\beta_j\left(1+\Psi^O+\Psi^S\right)}E^N+\frac{\Phi_j\sum\limits_{j\in S}\frac{1}{\beta_j}}{1+\Psi^O+\Psi^S}\left(E^N\right)^2-\frac{1}{2}\left(E^N\right)^2 \\
&= \left[\frac{\Phi_j\sum\limits_{j\in S}\frac{1}{\beta_j}-\Psi_j^S\left(1+\Psi^O\right)}{1+\Psi^O+\Psi^S}-\frac{1}{2}\right]\left(E^N\right)^2.
\end{aligned}$$

Same for the welfare changes of other members $k \neq j \in S$.

$$\begin{aligned}
\frac{dw(e_k^S)}{d\Phi_j} &= \beta_k\left(\bar{e_k}-e_k\right)\frac{de_k^S}{d\Phi_k}-\Phi_j\frac{dE^N}{d\Phi_j}E^N \\
&= -\beta_k\Psi_k^S E^N\frac{1+\Psi^O}{\beta_k\left(1+\Psi^O+\Psi^S\right)}E^N+\frac{\Phi_k\sum\limits_{j\in S}\frac{1}{\beta_j}}{1+\Psi^O+\Psi^S}\left(E^N\right)^2 \\
&= \frac{\Phi_k\sum\limits_{j\in S}\frac{1}{\beta_j}-\Psi_k^S\left(1+\Psi^O\right)}{1+\Psi^O+\Psi^S}\left(E^N\right)^2.
\end{aligned}$$

Note that $\frac{dw(e_k^S)}{d\Phi_j} < 0$ if $\Phi_k \sum\limits_{j\in S}\frac{1}{\beta_j} - \Psi_k^S\left(1+\Psi^O\right) < 0$, which is equivalent to $\Phi_k\beta_k < \frac{\Phi^S\left(1+\Psi^O\right)}{\sum_{j\in S}\frac{1}{\beta_j}}$. Thus, a member country that highly benefits from emissions (low β_k) and is less vulnerable to climate change (low Φ_k) is most likely to gain from technological progress in adaptation. Moreover, $\frac{dw(e_j^S)}{d\Phi_j} < \frac{dw(e_j^S)}{d\Phi_k}$, which implies a member country always gains more if the technological progress in adaptation is originated in the country.

Although the welfare change for individual member depends on each member's parameters, the welfare of the coalition always raises as a result of technological progress in adaptation adopted in any member country:

$$\sum_{k\in S}\frac{dw(e_k^S)}{d\Phi_j} \;=\; -\left(\frac{\Psi^O\Psi^S}{1+\Psi^O+\Psi^S}+\frac{1}{2}\right)\left(E^N\right)^2 < 0, j\in S.$$

Finally, a non-member's welfare decreases as a result of its reduced emissions level and the rising global emissions:

$$\begin{aligned}\frac{dw(e_i^O)}{d\Phi_j} &= \beta_i\left(\bar{e}_i - e_i\right)\frac{de_i^O}{d\Phi_j} - \Phi_j\frac{dE^N}{d\Phi_i}E^N \\ &= \frac{\left(1+\Psi_i\right)\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}}{1+\Psi^O+\Psi^S}\left(E^N\right)^2 > 0.\end{aligned}$$

□

A.1.3 Proof of Lemma 1

Proof. First, suppose a country i's α_i changes. A non-member i's emissions rise if its α_i increases:

$$\frac{\partial e_i^O}{\partial\alpha_i} = \frac{1}{\beta_i}\left(1-\frac{\Psi_i}{1+\Psi^O+\Psi^S}\right) > 0, i\in O.$$

For any other countries $k\neq i\in O$ and $j\in S$, the emissions reduces as a result of an increase in α_i:

$$\begin{aligned}\frac{\partial e_k^O}{\partial\alpha_i} &= -\frac{1}{\beta_i}\frac{\Psi_k}{1+\Psi^O+\Psi^S} < 0, k\neq i\in O \\ \frac{\partial e_j^S}{\partial\alpha_i} &= -\frac{1}{\beta_i}\frac{\Psi_j^S}{1+\Psi^O+\Psi^S} < 0, j\in S.\end{aligned}$$

Suppose a member j's α_j changes, then member j's emission level rises in response:

$$\frac{\partial e_j^S}{\partial \alpha_j} = \frac{1}{\beta_j}\left(1 - \frac{\Psi_j^S}{1 + \Psi^O + \Psi^S}\right) > 0, j \in S.$$

For any other countries, the emissions reduces as a result of an increase in α_j.

$$\frac{\partial e_k^S}{\partial \alpha_j} = -\frac{1}{\beta_j}\frac{\Psi_k^S}{1 + \Psi^O + \Psi^S} < 0, k \neq j \in S,$$
$$\frac{\partial e_i^O}{\partial \alpha_j} = -\frac{1}{\beta_j}\frac{\Psi_i}{1 + \Psi^O + \Psi^S} < 0, i \in O.$$

The global emission level always rises no matter which country experiences reduced α:

$$\frac{\partial E^N}{\partial \alpha_i} = \frac{1}{\beta_i\left(1 + \Psi^O + \Psi^S\right)} > 0, i \in N.$$

Second, suppose β changes in a country. If a non-member i's β_i drops, its emission level rises:

$$\frac{\partial e_i^O}{\partial \beta_i} = -\frac{1}{\beta_i}\left(1 - \frac{\Psi_i}{1 + \Psi^O + \Psi^S}\right) e_i^O.$$

$\frac{\partial e_i^O}{\partial \beta_i}$ is of the opposite sign of e_i. If the country emits in the non-cooperation equilibrium, improvement in marginal benefit will cause the country to emit more. If the country sequestrates emissions, a flatter marginal benefit will cause the country to sequestrate more.

For any other countries $k \neq i \in O$ and $j \in S$, the change in emissions can be derived as the following,

$$\frac{\partial e_k^O}{\partial \beta_i} = \frac{1}{\beta_i}\frac{\Psi_k}{1 + \Psi^O + \Psi^S} e_i^O,$$
$$\frac{\partial e_j^S}{\partial \beta_i} = \frac{1}{\beta_i}\frac{\Psi_j^S}{1 + \Psi^O + \Psi^S} e_i^O.$$

Since $\frac{\partial e_i^O}{\partial \beta_i}\frac{\partial e_k^O}{\partial \beta_i} \leq 0$, and $\frac{\partial e_i^O}{\partial \beta_i}\frac{\partial e_j^S}{\partial \beta_i} \leq 0$, emissions of other countries respond oppositely to country i.

The changes of global emission level is given by,

$$\frac{\partial E^N}{\partial \beta_i} = -\frac{1}{\beta_i\left(1+\Psi^O+\Psi^S\right)} e_i^O.$$

$\frac{\partial E^N}{\partial \beta_i}$ is of the same sign with $\frac{\partial e_i^O}{\partial \beta_i}$. Thus the global emission level goes the same direction as country i's emission changes.

Now suppose a member j's β_j drops. The member j increases its emission level:

$$\frac{\partial e_j^S}{\partial \beta_j} = -\frac{1}{\beta_j}\left(1-\frac{\Psi_j^S}{1+\Psi^O+\Psi^S}\right) e_j^S.$$

For any other countries, emissions respond oppositely to country j. The global emissions level goes to the same direction as country j's emission. These results are given by,

$$\begin{aligned}
\frac{\partial e_k^S}{\partial \beta_j} &= \frac{1}{\beta_j}\frac{\Psi_k^S}{1+\Psi^O+\Psi^S} e_j^S, k \neq j \in S,\\
\frac{\partial e_i^O}{\partial \beta_j} &= \frac{1}{\beta_j}\frac{\Psi_i}{1+\Psi^O+\Psi^S} e_j^S, i \in O,\\
\frac{\partial E^N}{\partial \beta_j} &= -\frac{1}{\beta_j\left(1+\Psi^O+\Psi^S\right)} e_j^S.
\end{aligned}$$

Additionally, from (1.16) adaptation level always goes to the same direction as the global emission level does. □

A.1.4 Proof of Lemma 2

Proof. Suppose $S = \varnothing$ [1] and $O = N$. $\Psi^O = \sum_{i\in N}\frac{\Phi_i}{\beta i} = \Psi$, and $\Psi^S = 0$. From (A.9),

$$E^N = \frac{\overline{E}}{1+\Psi^O+0} = \frac{\overline{E}}{1+\Psi} = E.$$

Suppose $S = N$ and $O = \varnothing$. $\Phi^O = 0$ and $\Phi^S = \sum_{j\in S}\frac{\Phi_j}{\beta_j} = \Psi^G$. From (A.15),

$$E^N = \frac{\overline{E}}{1+0+\Psi^S} = \frac{\overline{E}}{1+\Psi^G} = E^G.$$

[1] If S has only one element, $E^N = E$ as well. A country as the only signatory to an IEA behaves like a singleton. In this paper a valid coalition is defined as a treaty among two or more individuals.

To compare E, E^G and E^N,

$$\begin{aligned}
\frac{E^G}{E^N} &= \frac{1+\Psi^G}{1+\Psi^O+\Psi^S} \leq 1,\\
\frac{E^N}{E} &= \frac{1+\Psi^O+\Psi^S}{1+\Psi} \leq 1,\\
&\Rightarrow E^G \leq E^N \leq E.
\end{aligned}$$

From (1.15), the world's total emissions is given by,

$$E^N(S) = \frac{\overline{E}}{1+\Psi^O+\Psi^S}. \tag{A.1}$$

If any country $i \in O$ joins the coalition S, the global emissions becomes,

$$E^N(S \cup \{i\}) = \frac{\overline{E}}{1+\Psi^O+\Psi^S+\Psi_i^S+\Phi_i \sum_{k\in S}\frac{1}{\beta_k}}, \tag{A.2}$$

where $1+\Psi^O+\Psi^S+\Psi_i^S+\Phi_i \sum_{k\in S}\frac{1}{\beta_k} > 1+\Psi^O+\Psi^S$. Thus $E^N(S\cup\{i\}) < E^N(S)$. Since S can be any coalition, the global emission level decreases as the coalition has more members.

From (1.16), $a_i^G \leq a_i^N \leq a_i$, $\forall i \in N$. □

A.1.5 Proof of Lemma 3

Proof. From (1.19), $\Gamma_j^S(S) \geq 0$ is equivalent to the following,

$$\frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j} \geq \left(1-\frac{\Psi_j^S-2\Psi_j+\Phi_j\sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}\right)^2,$$

where $1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\}) = 1+\Psi^O+\Psi^S+2\Psi_j-\Psi_j^S-\Phi_j\sum_{k\in S}\frac{1}{\beta_k}$.

For a member j in S, from (1.14) and (1.17), the change in emissions is given by,

$$e_j^S(S)-e_j^O(S\backslash\{j\}) \quad = \quad \left(\frac{\Psi_j}{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})}-\frac{\Psi_j^S}{1+\Psi^O+\Psi^S}\right)\overline{E},$$

where $1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\}) = 1+\Psi^O+\Psi^S+2\Psi_j-\Psi_j^S-\Phi_j\sum_{k\in S}\frac{1}{\beta_k}$.

$$
\begin{aligned}
e_j^S(S) > e_j^O(S\backslash\{j\}) \quad &\Leftrightarrow \quad \frac{\Psi_j}{\Psi_j^S} > \frac{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})}{1+\Psi^O+\Psi^S} \\
&\Leftrightarrow \quad \frac{\Phi_j}{\Phi^S} > 1 - \frac{\Psi_j^S - 2\Psi_j + \Phi_j \sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}.
\end{aligned}
$$

Since $\frac{\Phi_j}{\Phi^S} < 1$, $\frac{\Phi_j^2}{(\Phi^S)^2} < \frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j}$.

$$
\frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j} > \frac{\Phi_j^2}{(\Phi^S)^2} \geq \left(1 - \frac{\Psi_j^S - 2\Psi_j + \Phi_j \sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}\right)^2
$$

Hence, $\Gamma_j^S(S) > 0$. □

A.1.6 Proof of Lemma 4

Proof. Suppose a coalition exists, $S \neq \varnothing$. From (A.7) and (1.13),

$$
\begin{aligned}
&e_i^O(S) - e_i = \left(\frac{1}{1+\Psi} - \frac{1}{1+\Psi^O+\Psi^S}\right)\Psi_i\overline{E}, i \in O, \\
&1+\Psi^O+\Psi^S = 1+\Psi+\sum_{j\in S}\left(\Psi_j^S - \Psi_j\right) > 1+\Psi, \\
&\Rightarrow e_i^O(S) > e_i.
\end{aligned}
$$

From (A.7) and (1.14),

$$
\begin{aligned}
&e_j^S(S) - e_j = \left(\frac{\Psi_j}{1+\Psi} - \frac{\Psi_j^S}{1+\Psi^O+\Psi^S}\right)\overline{E}, j \in S, \\
&e_j^S(S) \geq e_j \Leftrightarrow \frac{\Phi_j}{\Phi^S} \geq \frac{1+\Psi}{1+\Psi^O+\Psi^S}.
\end{aligned}
$$

From Lemma 2, $E^N < E$ if $S \neq \varnothing$.

$$
\begin{aligned}
E^N(S) &= E^O(S) + E^S(S) = \sum_{i\in O} e_i^O(S) + \sum_{j\in S} e_j^S(S), \\
E &= \sum_{i\in O} e_i + \sum_{j\in S} e_j.
\end{aligned}
$$

We have already proven that $e_i^O(S) > e_i, \forall i \in O$, and hence $\sum_{i \in O} e_i^O(S) > \sum_{i \in O} e_i$. Thus $E^S(S) < \sum_{j \in S} e_j$. $\square$

A.1.7 Emissions and cooperative incentives

From A.1.5 (the proof of Lemma 3), conditions defining the three types of countries in a coalition can be derived and is given in the following table.

Type	Relation	Emission Change	Cooperative Incentives
Strong-cooperative	$\left(1-\frac{\Psi_j^S-2\Psi_j+\Phi_j\sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}\right)^2 \leq \frac{\Phi_j^2}{(\Phi^S)^2} < \frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j}$	$e_j^S(S) \geq e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) > 0$
Weak-cooperative	$\frac{\Phi_j^2}{(\Phi^S)^2} < \left(1-\frac{\Psi_j^S-2\Psi_j+\Phi_j\sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}\right)^2 \leq \frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j}$	$e_j^S(S) < e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) \geq 0$
Non-cooperative	$\frac{\Phi_j^2}{(\Phi^S)^2} < \frac{\Phi_j^2+\beta_j\Phi_j}{(\Phi^S)^2+\beta_j\Phi_j} < \left(1-\frac{\Psi_j^S-2\Psi_j+\Phi_j\sum_{k\in S}\frac{1}{\beta_k}}{1+\Psi^O+\Psi^S}\right)^2$	$e_j^S(S) < e_j^O(S\backslash\{j\})$	$\Gamma_j^S(S) < 0$

Table A.1: Emission changes and cooperative incentives

A.1.8 Disparity in Vulnerability and Proof of Proposition 3

Proof. For a given coalition, all coalition-level parameters, i.e. Φ^O, Φ^S, Ψ^O and Ψ^S, are fixed. Thus the cooperative incentive of any member in the coalition is a function of that member's parameters. Specifically, let j be any arbitrary member in the coalition, and its cooperative incentive depends β_j and ϕ_j.

$$\frac{\partial \Gamma_j^S(\Phi_j,\beta_j;S)}{\partial \Phi_j} = \frac{\overline{E}^2}{2}\left[2\Psi_j\frac{1+\Psi^O+\Psi^S-(1+\Psi_j)(2-\sum_{k\in S}\frac{\beta_j}{\beta_k})}{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})^3}\right.$$
$$\left.+\frac{1}{1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})^2}-\frac{1}{(1+\Psi^O+\Psi^S)^2}\right]$$

Since $(1+\Psi_j)(2-\sum_{k\in S}\frac{\beta_j}{\beta_k}) < (1+\Psi_j) < 1+\Psi^O+\Psi^S$, the first term in the square brackets is positive. Also note that $1+\Psi^O+\Psi^S > 1+\Psi^O(S\backslash\{j\})+\Psi^S(S\backslash\{j\})$. The second and third term together is positive. Therefore, $\frac{\partial\Gamma_j^S(\Phi_j,\beta_j;S)}{\partial\Phi_j} > 0$, i.e. the higher the net vulnerability a member has, the higher cooperative incentives. If two signatories have the same β, whoever is more vulnerable has more incentives to cooperate.

From (1.19), if there exists at least one member j with relatively low vulnerability, such that

$$\frac{\Phi_j^2 + \beta_j \Phi_j}{(\Phi^S)^2 + \beta_j \Phi_j} < \frac{\left[1 + \Psi^O(S \backslash \{j\}) + \Psi^S(S \backslash \{j\})\right]^2}{(1 + \Psi^O + \Psi^S)^2},$$

$\Gamma_j^S(S) < 0$, which implies its cooperation incentive is negative and the coalition is not stable.

□

Let us look at a simple case with an IEA that consists only two countries. For a given agreement, all coalition-level parameters are fixed, and countries differ in their net vulnerability. Suppose the two countries' vulnerability does not differ much from each other (every country's vulnerability is close to the average level), as shown in Fig.(A.1); all countries may have positive cooperative incentives as their vulnerability is close to the average vulnerability Φ^m. However, if two countries substantially differ from each other in vulnerability, for example, as the Φ^L and Φ^H in Fig.(A.1), the one with low vulnerability becomes 'non-cooperative' and will choose to stay outside the coalition. Hence a stable coalition cannot be formed if members differ much in vulnerability.

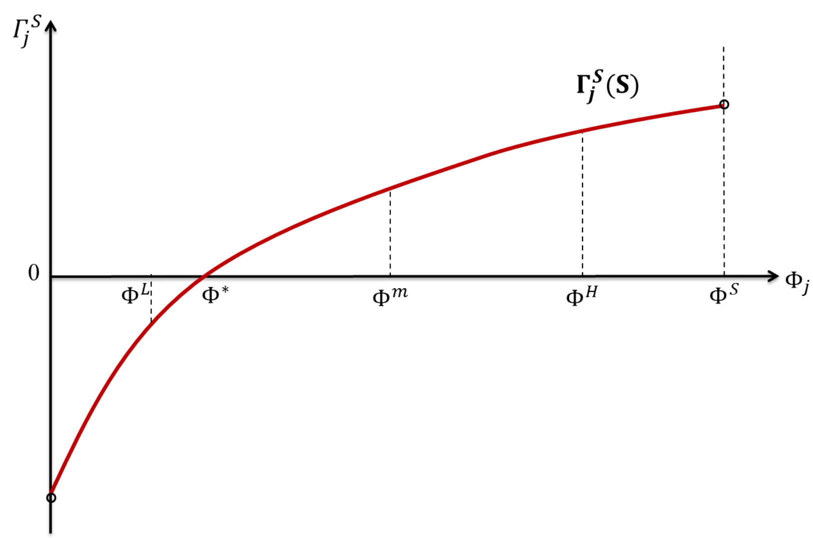

Figure A.1: Cooperative incentives for member countries

A.1.9 Proof of Proposition 4

Proof. The emission levels of country i outside and inside of the existing coalition are given by,

$$\begin{aligned} e_i^O(S) &= \overline{e_i} - \frac{\Psi_i}{1+\Psi^O+\Psi^S}\overline{E} \\ e_i^S(S\cup\{i\}) &= \overline{e_j} - \frac{\Psi_i^S + r_i\Psi_i}{1+\Psi^O+\Psi^S+\Psi_i^S+r_i\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+r_i\Psi_i-\Psi_i}\overline{E} \end{aligned}$$

The free riding incentive is given as the following,

$$\Gamma_i^O(S) = \frac{\beta_i\overline{E}^2}{2}\left[\frac{(\Psi_i^S+r_i\Psi_i)^2+r_i\Psi_i}{(1+\Psi^O+\Psi^S+\Psi_i^S+r_i\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+r_i\Psi_i-\Psi_i)^2} - \frac{\Psi_i^2+\Psi_i}{(1+\Psi^O+\Psi^S)^2}\right] \tag{A.3}$$

Take derivative of Γ_i^O with respect to r_i,

$$\begin{aligned} \frac{\partial\Gamma_i^O}{\partial r_i} = \frac{\beta_i\overline{E}^2}{2}\Bigg\{ & \frac{2\Psi_i(\Psi_i^S+r_i\Psi_i)+\Psi_i}{(1+\Psi^O+\Psi^S+\Psi_i^S+r_i\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+r_i\Psi_i-\Psi_i)^2} \\ & - \frac{2[(\Psi_i^S+r_i\Psi_i)^2+r_i\Psi_i](\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+\Psi_i)}{(1+\Psi^O+\Psi^S+\Psi_i^S+r_i\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+r_i\Psi_i-\Psi_i)^3}\Bigg\}. \end{aligned}$$

Hence, the condition on which $\frac{\partial\Gamma_i^O}{\partial r_i} > 0$ holds is given by,

$$\frac{2\Psi_i(\Psi_i^S+r_i\Psi_i)+\Psi_i}{2[(\Psi_i^S+r_i\Psi_i)^2+r_i\Psi_i]} > \frac{\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+\Psi_i}{(1+\Psi^O+\Psi^S+\Psi_i^S+r_i\Phi_i\sum\limits_{j\in S}\frac{1}{\beta_j}+r_i\Psi_i-\Psi_i)}.$$

As $\beta_i \to +\infty$, the limits of left and right hand side are given as following,

$$\begin{aligned} \lim_{\beta_i\to+\infty} LHS &= \frac{1}{2r_i}, \\ \lim_{\beta_i\to+\infty} RHS &= 0. \end{aligned}$$

If in general $\beta_i >> \Phi_i$ for all $i \in N$, LHS $=\frac{1}{2r_i} >$ RHS $= 0$, and $\frac{\partial\Gamma_i^O}{\partial r_i} > 0$.

Since the coalition S is arbitrary, the free-riding incentive of any country is negatively related with its adoption cost of the new technology if $\beta_i >> \Phi_i$, $\forall i \in N$.

$\square$

From (A.7), (A.8), and (A.9), the welfare for a country i is given by:

$$\begin{aligned} w\left(e_i, a_i, E\right) &= B(e_i) - D\left(E, a_i\right) - C\left(a_i\right) \\ &= \alpha_i e_i - \frac{\beta_i}{2} e_i^2 - \frac{\Phi_i}{2} E^2 \\ &= \frac{\alpha_i}{2} \bar{e_i} - \frac{\Phi_i}{2} \frac{1+\Phi_i}{(1+\Phi)^2} \bar{E}^2 \end{aligned}$$

If Φ_i is very large, the net welfare generated from emissions is negative. However, the damage from climate change is considered to be much smaller than the GDP generated from emissions. Thus, the opposite case of $\beta_i >> \Phi_i$ is a trivial one. Note that even if the benefit and damage are of the similar amount, β is expected to be much larger than Φ since benefit is generated by private emissions, while damage is based on aggregate emissions of all countries. Indeed, β_i is much larger than Φ_i for all countries as shown in our numerical example.

A.2 Two Polar Cases

Note: This material has been developed in many of the existing papers in the literature and is only provided here for context and as a benchmark.

A.2.1 The Non-cooperative Outcome

In the non-cooperative outcome, each country chooses emission (e_i) and adaptation (a_i) levels to maximize its own welfare, taking as given other countries' emissions:

$$\max_{e_i, a_i} w\left(e_i, a_i, E\right) = B(e_i) - D\left(E, a_i\right) - C\left(a_i\right). \tag{A.4}$$

Solving for the best response functions of emissions and adaptation for country i yields:

$$e_i = \frac{\alpha_i - \Phi_i E_{-i}}{\beta_i + \Phi_i} \tag{A.5}$$

$$a_i = \frac{\theta_i}{c_i} \left(\frac{\alpha_i + \beta_i E_{-i}}{\beta_i + \Phi_i} \right), \tag{A.6}$$

where $\Phi_i \equiv v_i - \frac{\theta_i^2}{c_i}$ is the net vulnerability in the presence of adaptation. Substituting a_i from (A.6) into (1.2), we obtain the net marginal damage from emissions: $\frac{dD(E)}{dE} = \Phi_i E$, where Φ_i is always positive from (1.4). Note that as a result of technological progress in adaptation in country i, θ_i rises and/or c_i drops and country i's net vulnerability decreases.

We add up (A.5) for all countries to derive global emissions and country i's emission and adaptation level, which are given by,

$$e_i = \overline{e_i} - \frac{\Psi_i}{1+\Psi}\overline{E} \tag{A.7}$$

$$a_i = \frac{\theta_i}{c_i}E, \tag{A.8}$$

where $\Psi_i \equiv \frac{\Phi_i}{\beta_i}$ and $\Psi \equiv \sum_{k \in N} \Psi_k$. Note that Φ_i is the rate of change for (net of adaptation) marginal damage from emissions, while β_i is the rate of change for marginal benefit of emissions. Therefore, Ψ_i is the relative rate of change for marginal damage to marginal benefit. A country's emission level, as given by (A.7), is equal to its maximum emission level minus its abatement level. In the second term, Ψ_i is a country-specific 'abatement indicator': a country with a larger Ψ_i (i.e. larger Φ_i and/or smaller β_i) abates more. A highly vulnerable country chooses a high abatement level to reduce the damage from climate change. Moreover, since β_i can be interpreted as the rate of change of the marginal cost of abatement, a country with a lower β_i has a marginal cost of abatement that increases more slowly with abatement, and hence abates more emissions. From (A.7), one can see that abatement is undertaken even though no IEA is formed since natural vulnerability to climate change cannot be neutralized by adaptation ($\Phi_i > 0$).[2]

The global emission level is given by,

$$E = \frac{\sum_{k=1}^{n} \frac{\alpha_k}{\beta_k}}{1 + \sum_{k=1}^{n} \frac{\Phi_k}{\beta_k}} = \frac{1}{1+\Psi}\overline{E}, \tag{A.9}$$

where $\overline{E} \equiv \sum_{k \in N} \overline{e_k} = \sum_{k \in N} \frac{\alpha_k}{\beta_k}$ is the maximum level of the world's emissions. The fraction multiplying $\overline{E}$ is decreasing in Ψ and thus - as expected - the actual aggregate emission are lower when countries (and the world as a whole) have higher 'abatement indicators'.[3] From (A.7), (A.8) and (A.9), any change in the abatement indicator Ψ_i in a country, i.e. β_i and Φ_i, can affect emission and adaptation levels in all countries. Our assumption of

[2] In the extreme case that the damage can be fully countered by adaptation (i.e. $\Phi_i = 0$), the country does not abate (its abatement factor $\Psi_i \equiv \frac{\Phi_i}{\beta_i} = 0$), and its emissions achieve the maximum level $\overline{e_i}$.

[3] Alternatively, note that $\frac{1}{1+\Psi} = 1 - \frac{\Psi}{1+\Psi}$ decreases with $\frac{\Psi}{1+\Psi}$ which is the fraction of total emissions mitigated by all countries.

heterogeneous countries allows us to investigate the impact of a change in Φ_i as a result of technological progress in adaptation in a country on its own emission levels as well as others'.

A.2.2 Fully-cooperative Outcome (The Grand Coalition)

Suppose all nations are signatories of the IEA. All countries choose simultaneously e_i and a_i to maximize the joint welfare,

$$\max_{e_i,a_i} \sum_{i\in N} w\left(e_i, a_i, E\right) = \sum_{i\in N} \left[B(e_i) - D\left(E, a_i\right) - C\left(a_i\right)\right] \tag{A.10}$$

The best response functions for a country i are given by,

$$e_i = \frac{\alpha_i - \sum\limits_{k\in N} \Phi_k E_{-i}}{\beta_i + \sum\limits_{k\in N} \Phi_k} \tag{A.11}$$

$$a_i = \frac{\theta_i}{c_i}\left(\frac{\alpha_i + \beta_i E_{-i}}{\beta_i + \sum\limits_{k\in N} \Phi_k}\right) \tag{A.12}$$

The global emissions and the individual emission levels can be derived from (A.11) and (A.12). Country i's emission and adaptation level are given by:

$$e_i^G = \overline{e_i} - \frac{\Psi_i^G}{1+\Psi^G}\overline{E} \tag{A.13}$$

$$a_i^G = \frac{\theta_i}{c_i}E^G \tag{A.14}$$

where $\Psi_i^G \equiv \frac{\Phi}{\beta_i}$.[4] Similar to (A.7), the second term in (A.13) is the abatement level. However, a country's abatement indicator Ψ_i^G in (A.13) is much larger than in the non-cooperation case Ψ_i since it takes the joint vulnerability Φ into account instead of its own vulnerability Φ_i.

The full-cooperation level of global emissions is given by the following,

$$E^G = \frac{1}{1+\Psi^G}\overline{E}, \tag{A.15}$$

where $\Psi^G \equiv \sum\limits_{k\in N} \Psi_k^G$ is the global abatement indicator under the grand coalition.

[4] Superscript 'G' denotes the 'grand coalition'.

A.3 Simulation Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP (Million US $)	7062	120000.00	695000.00	9.12	15000000.00
totalGHG (kt of CO2 equivalent)	8772	97168.53	486456.30	-80.67	10800000.00
Climate_change_cost (Million US $)	172	3510.00	10600.00	5.00	90000.00

Table A.2: Summary statistics

	α_i	β_i	Φ_i
1	2726563.75	254.92	0.000535
2*	832838.63	0.45	0.026759
3	1210438.38	4.83	0.002007
4*	1530063.75	6.58	0.009366
5*	232675760.00	6619563.00	0.000040
6*	6543675.50	4941.58	0.000401
7	955863.94	1.88	0.004014
8	1054546.00	43.55	0.000937
9	1908327.88	33.74	0.001003
10	444350.00	12.30	0.000669

*: countries in the largest stable coalition

Table A.3: Estimated parameters

	World's emissions (kt of CO2 equivalent)	Welfare (Million US$)
Non-cooperative equilibrium	2777422.04	1250495.90
Full-cooperative equilibrium	2572505.81	1259387.99
With stable coalition {2,4,5,6}	2711780.17	1253297.08

*: compared to the non-cooperative equilibrium

Table A.4: World's emissions and welfare

Appendix B

The Appendix for Chapter 2

B.1 Patent Search Criteria

“Flood” is a commonly used words in many disciplines and industries other than the natural disaster “flood” (e.g., printing, radiation imagery chemistry, and information security). Irrelevant patents can be excluded by restricting classes to search. Therefore, all search criteria for flood impact-reducing patents consist keywords and classes. Three criteria are established for flood (Table B.1): the main criterion for patents pertaining to floods, and also criterion 1 and 2. The use of ”drought” and ”earthquake” is much more specific to natural disasters, and hence restricting classes is not necessary. Patent counts calculated from each criteria are applied to Eq. (2.3) and (2.4) with Poisson FE model to check robustness, and results are reported in Table B.2. The results from criterion 1 and 2 are consistent with the finds using the main criteria. Patents pertaining to flood positively respond to national flood damage in the U.S. Additionally, there is no evidence that flood impact-reducing patents respond to local floods.

Table B.1: Patent search criteria for floods, droughts and earthquakes

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

Table B.2: Patent counts in response to national and state-level flood damage

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

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

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

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

Table B.3: Summary of variables at the state level

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

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

B.2 Maps of Patents and Disaster Damage

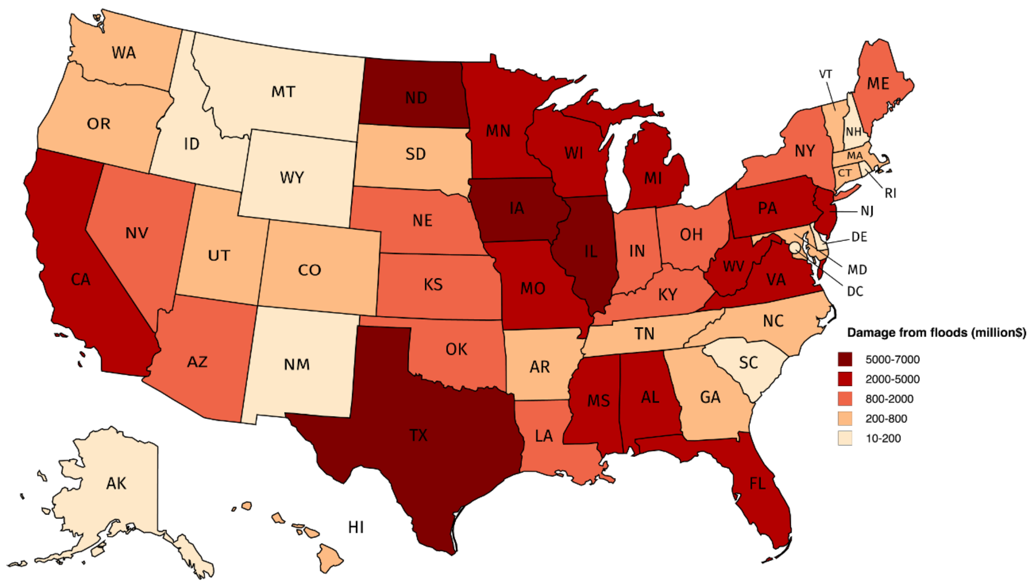

Figure B.1: Map of flood damage across states from 1977-2005

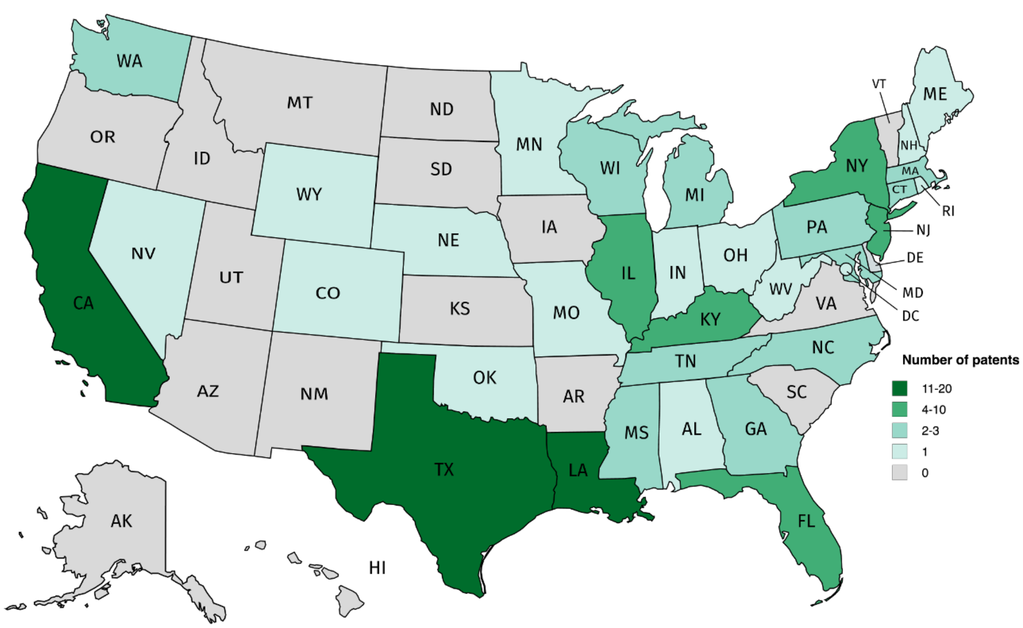

Figure B.2: Map of flood impact-reducing patents across states from 1977-2005

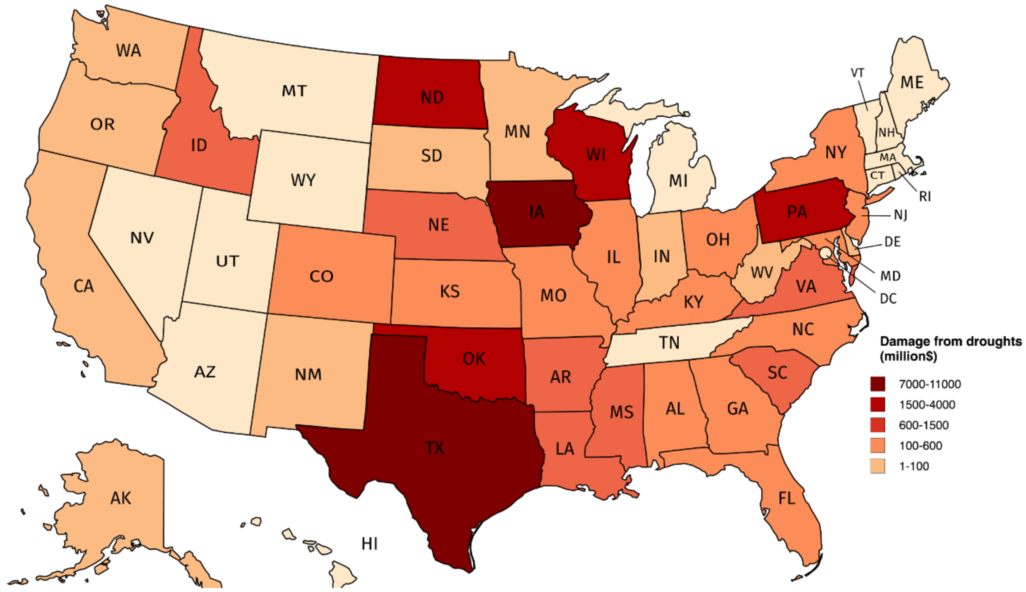

Figure B.3: Map of drought damage across states from 1977-2005

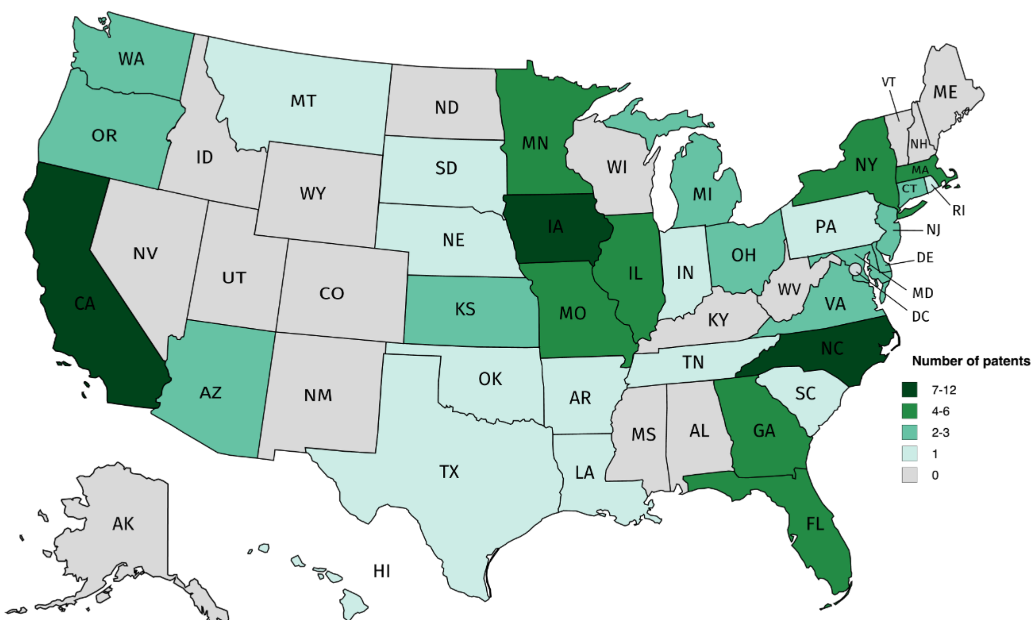

Figure B.4: Map of drought impact-reducing patents across states from 1977-2005

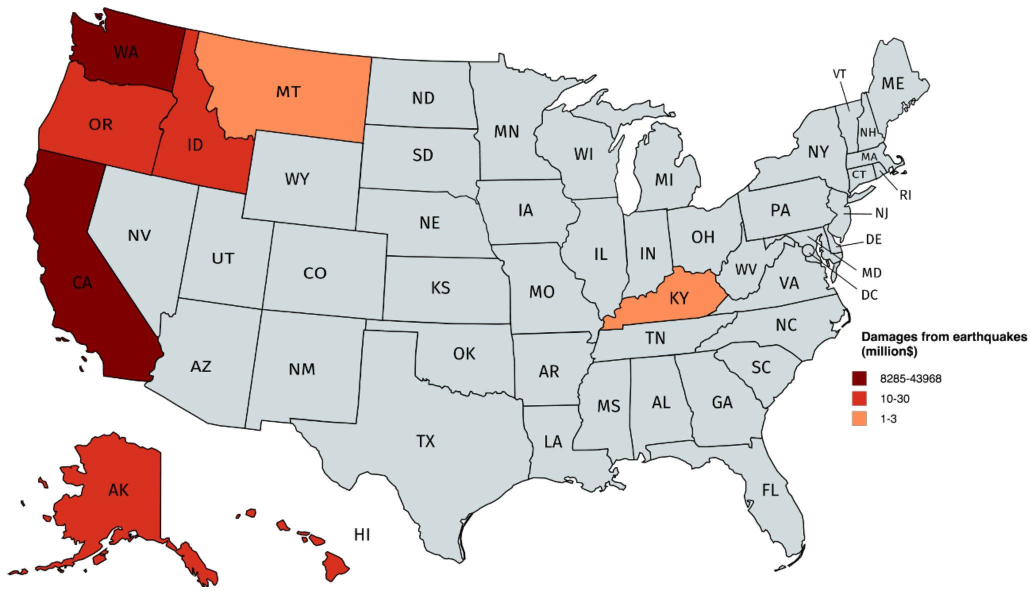

Figure B.5: Map of earthquake damage across states from 1977-2005

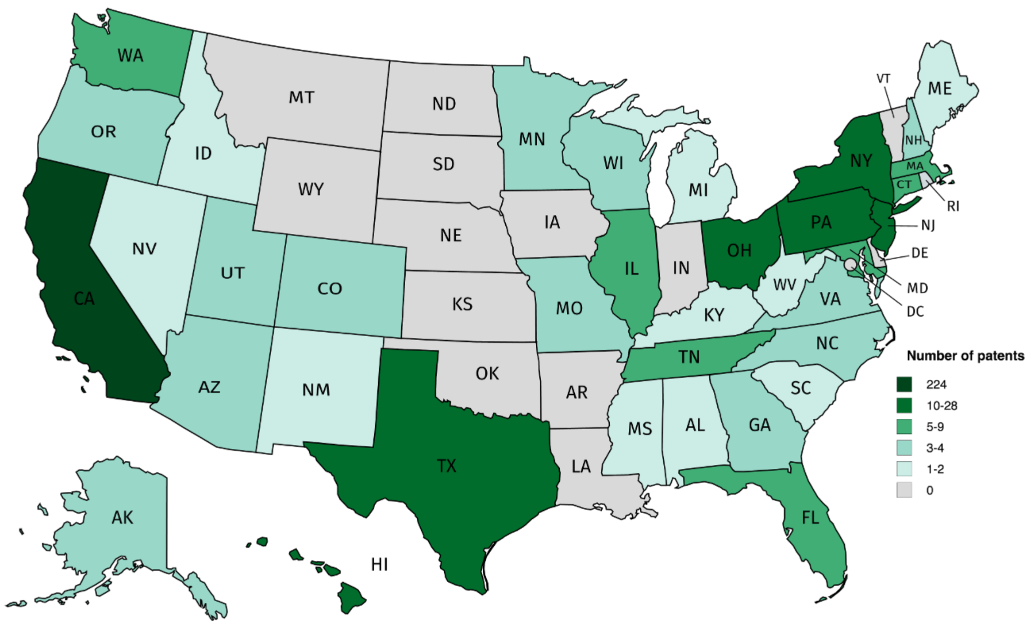

Figure B.6: Map of earthquake impact-reducing patents across states from 1977-2005

B.3 IV Tests and the Control Function Approach

Table B.4: Control functions for flood damage

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

Standard errors in parentheses

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

Table B.5: Control functions for drought and earthquake damage

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

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

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

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

B.4 Fatalities as a Measure of Disaster Damage

Impact-reducing patent applications respond to national aggregated fatalities. The results are reported in Table B.6 and B.7. There is strong evidence that impact-reducing patent applications positively respond to national aggregate fatalities for floods and earthquakes. However, patents pertaining to droughts do not positively respond to drought fatalities due to a small number of fatalities from drought in the U.S.

B.5 Innovation in Response to the Regional Disaster Damage

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

Here, the basic model (2.2) is extended to a region including a state and its neighboring states. Innovation in a given state is modeled as a function of regional disaster damage, controlling for other factors:

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

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

Eq. (B.1) is estimated with the Poisson FE model, and the results for floods, droughts and earthquakes are reported in Table B.8. For droughts and floods, there is no evidence that impact-reducing patents respond to disaster damages in the neighboring states, whereas the cumulative effects of disaster damage in non-bordering states are positive and significant. This result further enhances the previous finding that the response of impact-reducing innovations is national in scope for floods and droughts. For earthquakes, the cumulative effect of aggregate damage from the nearby states is positive and significant, in

Table B.6: Response of patents to national disaster fatalities

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

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

Table B.7: Response of patents to fatalities from disasters in a state

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

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

Table B.8: Patent counts in response to regional disaster damage

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

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

contrast to the insignificant impacts of damage in non-bordering states. Combining previous findings, the response of earthquake impact-reducing innovations is mostly localized to the nearby region of an earthquake event.

B.6 GMM IV methods

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

However, one major drawback of GMM estimators is computational complexity, and availability of estimates is subject to variation in the data and model complexity, which is the case in this study. First, the relatively large number of zeros in the dependent variable for patents in a state appears to make it computationally difficult to exploit the moment conditions that this estimator relies on. Second, for a distributed lag model like Eq.(2.3) and (2.4), the moment condition contains information of lags of endogenous variables and lags of all IVs. For instance, five-year lags of flood damage is accompanied by five-year lags of the two IVs for flood, the total number of ten IVs. This dramatically increase computational complexity, and more importantly, reduce validity of IVs (disaster intensity in year s almost have no correlation with disaster damage in year t , for $t \neq s$). As a result, many of the above GMM IV estimators are not convergent with Eq.(2.3) and (2.4). Table B.9 reports available estimates on national flood, drought, and earthquake damage. The overall results support the finding that innovation in a state responds to natural disasters.

Table B.9: Response of patents to national disaster damage

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

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

Appendix C

The Appendix for Chapter 3

C.1 Overdispersion and Zero Counts

The discrete densities of dependent variables in three water issues are plotted in Figure C.1, C.2, and C.3. In general, the proportions of zero counts are 40-65% in the dependent variables of the three water issues. Given the large number of zeros, zero-inflated poisson (ZIP) and zero-inflated negative binomial (ZINB) models are employed to address excessive zero counts and potential overdispersion. The regression results for three water issues (i.e. drinking water quality, water pollution, and water quantity) are reported in column (3) and (4) of Table C.1, C.2, and C.3.

In addition, the Poisson quasi-maximum likelihood estimator (Poisson QMLE) has been widely used in count data literature (Blume-Kohout, 2012; Cameron & Trivedi, 2013; Hovhannisyan & Keller, 2015) due to its robustness to distributional misspecification (e.g., the dependent variable conditional on the explanatory variables does not have a Poisson distribution). As a comparison, the NB model is employed to address the potential overdispersion caused by excessive zeros. The results are presented in column (1) and (2) of Table C.1, C.2, and C.3 for three water issues.

In general, the results confirm the findings using Poisson FE and NB FE models. The Poisson FE and NB FE models fit better than other Poisson MLE, NB, ZIP, and ZINB in all three cases, according to the AIC and BIC. For example, the AIC and BIC scores are 819.56 and 920.69 for Poisson FE model applied to Eq. (3.1), which are smaller than all values of AIC and BIC reported in Table C.1. A likely reason is that the excessive zeros and potential overdispersion largely attribute to the cross-state variation. In terms of water technology, there is substantial state-level variation of innovations. For instance, Arkansas has zero patent count (search by Criterion 1 of drinking water technology) over time, while California has few zero count cross years. Therefore, fixed effect models that capture the cross-state variation provide better fit. Moreover, overdispersion is not likely to be a concern after controlling the state fixed effect. Although from Table 3.4, the unconditional variances is larger than the means, the conditional variance is very likely to be substantially reduced since cross-state variation are controlled.[1]

C.1.1 Drinking Water Quality

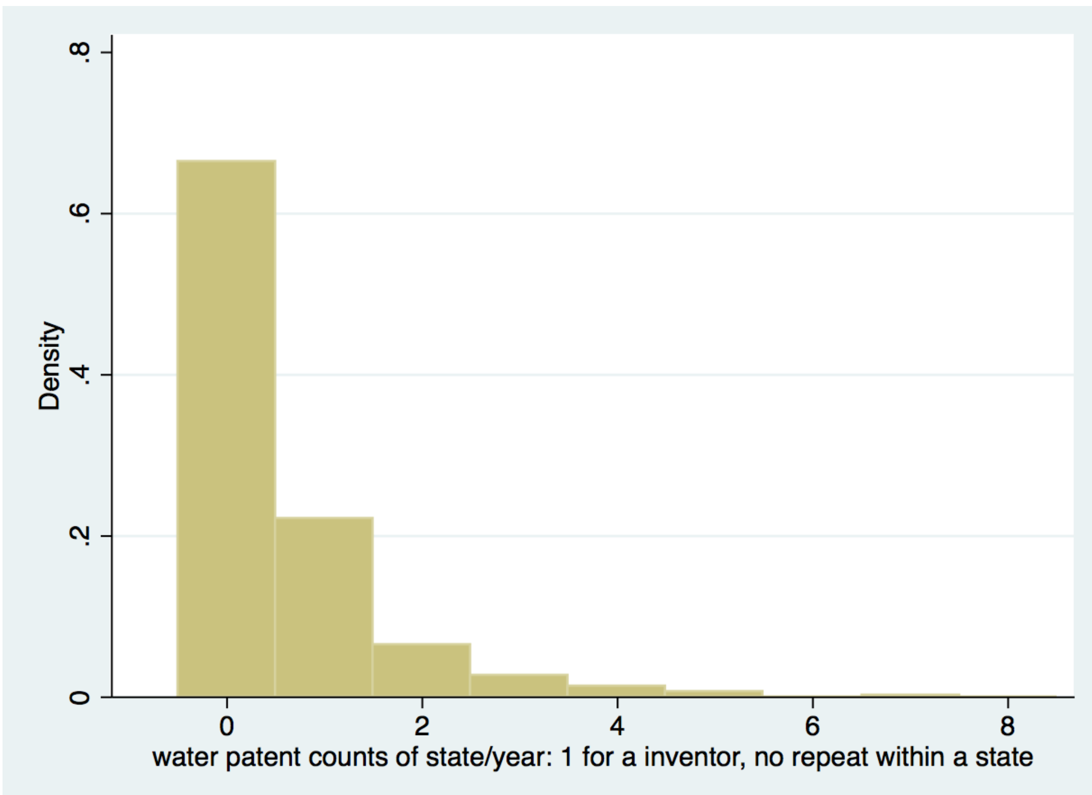

Figure C.1: Histogram of patents pertaining to drinking water technology

[1] According to Cameron & Trivedi (2013), the conditional mean remains similar to the unconditional mean. However, the conditional variance is usually smaller than the unconditional mean, especially when cross-group or cross-time variation are controlled.

Table C.1: Patent counts (Criterion 1) in response to drinking water regulations

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
pat4_3				
L1sdwa_newreg	0.535	0.545	0.479	0.487
	(0.386)	(0.375)	(0.309)	(0.311)
L2sdwa_newreg	0.291	0.276	0.298	0.295
	(0.299)	(0.306)	(0.318)	(0.315)
L3sdwa_newreg	0.535	0.494	0.539	0.526
	(0.336)	(0.343)	(0.345)	(0.348)
L4sdwa_newreg	0.582	0.556	0.549	0.541
	(0.339)	(0.353)	(0.344)	(0.347)
L5sdwa_newreg	0.373	0.351	0.359	0.353
	(0.450)	(0.457)	(0.411)	(0.413)
Cumulative effect	2.315*	2.222	2.223*	2.203*
	(1.203)	(1.226)	(1.078)	(1.084)
L1sdwa_revised	-0.441	-0.430	-0.415	-0.416
	(0.336)	(0.330)	(0.333)	(0.330)
L2sdwa_revised	0.117	0.145	0.0896	0.0987
	(0.303)	(0.322)	(0.289)	(0.297)
L3sdwa_revised	0.198	0.218	0.0783	0.0863
	(0.285)	(0.292)	(0.293)	(0.294)
L4sdwa_revised	0.344	0.385	0.208	0.228
	(0.338)	(0.356)	(0.341)	(0.358)
L5sdwa_revised	0.243	0.267	0.210	0.218
	(0.370)	(0.388)	(0.361)	(0.366)
Cumulative effect	0.461	0.584	0.171	0.215
	(0.847)	(0.910)	(0.831)	(0.843)
L1sdwa_amend	0.280	0.322	0.273	0.287
	(0.331)	(0.317)	(0.346)	(0.337)
L2sdwa_amend	0.627	0.596	0.622	0.611
	(0.432)	(0.429)	(0.370)	(0.373)
L3sdwa_amend	0.399	0.379	0.347	0.345
	(0.342)	(0.336)	(0.377)	(0.370)
L4sdwa_amend	0.339	0.372	0.285	0.298
	(0.272)	(0.275)	(0.255)	(0.259)
L5sdwa_amend	0.211	0.231	0.203	0.209
	(0.294)	(0.303)	(0.274)	(0.273)
Cumulative effect	1.857*	1.900**	1.731*	1.749*
	(0.753)	(0.929)	(0.903)	(0.920)
N	1479	1479	1479	1479
AIC	971.3	973.1	926.0	975.7
BIC	1156.8	1169.2	1016.0	1198.3
Log lik.	-450.7	-449.6	-446.0	-445.9

All regressions control for total number of patents, per capita GDP, higher education R&D expenditures, R&D tax credit rates, and state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. The cumulative effect of *sdwa_newreg* in (2) is significant at 10% level. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.1.2 Water Pollution

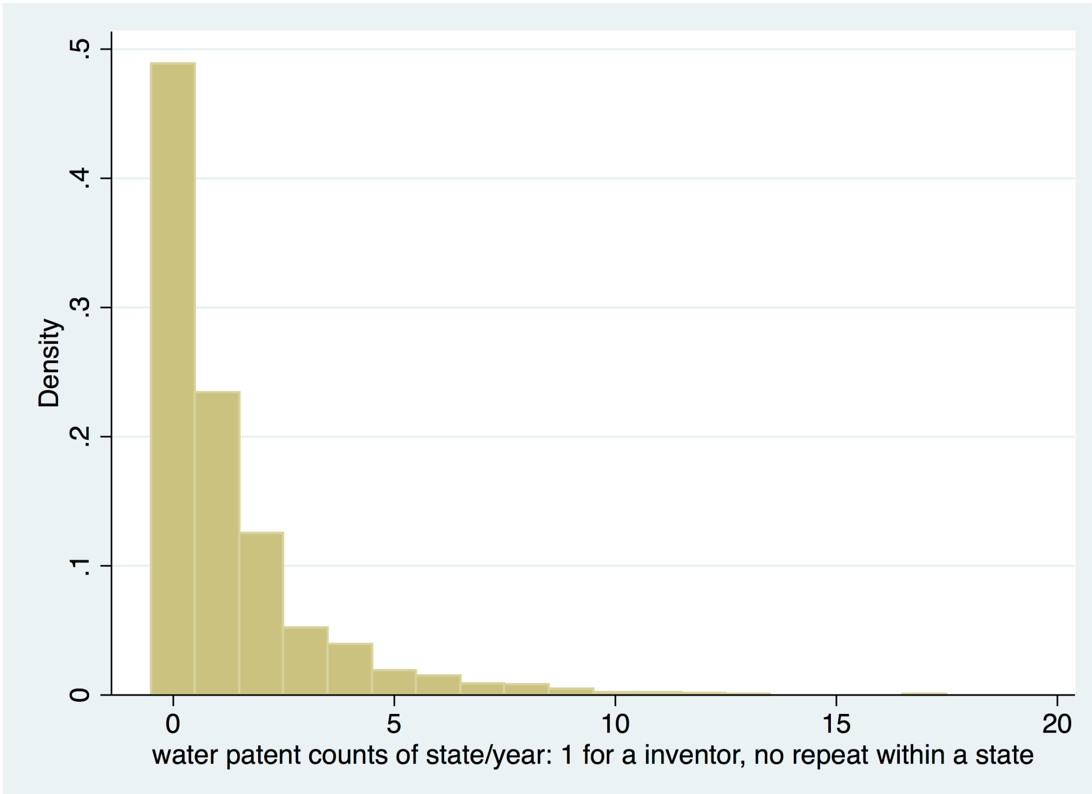

Figure C.2: Histogram of patents pertaining to water pollution treatment technology

Table C.2: Patent counts (Criterion 1) in response to the CWA amendments

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
cwa_amendcum	0.277**	0.270**	0.271**	0.271**
	(0.0891)	(0.0926)	(0.0880)	(0.0880)
pcrealGDP	0.0116	0.0120	0.00859	0.00860
	(0.0345)	(0.0349)	(0.0338)	(0.0338)
patcount	0.00740	0.00754	0.00414	0.00414
	(0.0301)	(0.0307)	(0.0296)	(0.0296)
rd_cr_st$_{t-1}$	0.111	0.114	0.118	0.118
	(0.0915)	(0.0979)	(0.111)	(0.111)
t_edurdexpdf$_{t-1}$	-0.161	-0.163	-0.132	-0.132
	(0.232)	(0.233)	(0.229)	(0.229)
post_97	0.0129	-0.00234	0.0783	0.0781
	(0.643)	(0.650)	(0.642)	(0.642)
N	1479	1479	1479	1479
AIC	1079.0	1072.5	1076.7	1068.7
BIC	1227.4	1205.0	1225.0	1195.8
Log lik.	-511.5	-511.3	-510.3	-510.3

All regressions control state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.1.3 Water Quantity

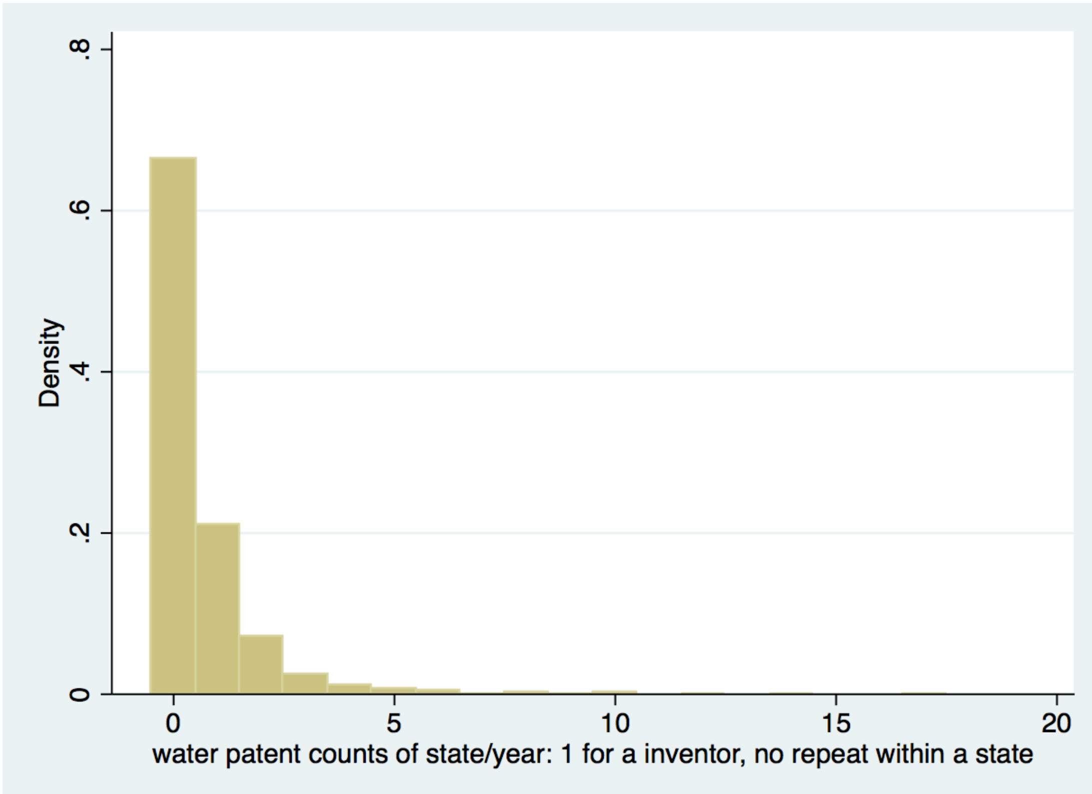

Figure C.3: Histogram of patents pertaining to water supply and demand technology

Table C.3: Patent counts (Criterion 1) in response to water planning and water scarcity

	(1) Poisson QMLE	(2) NB	(3) ZIP	(4) ZINB
L1waterplannew	0.139	0.0638	0.107	0.0880
	(0.346)	(0.433)	(0.347)	(0.434)
L2waterplannew	0.123	0.0756	0.136	0.110
	(0.243)	(0.295)	(0.241)	(0.291)
L3waterplannew	0.706^{*}	0.611	0.885^{*}	0.662
	(0.311)	(0.371)	(0.380)	(0.385)
L4waterplannew	0.333^{*}	0.269	0.348	0.316
	(0.167)	(0.250)	(0.183)	(0.268)
L5waterplannew	0.393	0.424	0.370	0.439
	(0.229)	(0.281)	(0.225)	(0.267)
Cumulative effect	1.694^{*}	1.444	1.846^{*}	1.615
	(0.775)	(1.032)	(0.886)	(1.080)
L1tdmg_c	0.0734	0.0656	0.0644	0.0652
	(0.0430)	(0.0470)	(0.0391)	(0.0554)
L2tdmg_c	0.0993^{*}	0.0820	0.0872^{*}	0.0806
	(0.0398)	(0.0522)	(0.0360)	(0.0686)
L3tdmg_c	0.105^{***}	0.0978^{**}	0.0946^{***}	0.0931^{**}
	(0.0288)	(0.0329)	(0.0267)	(0.0342)
L4tdmg_c	0.0520	0.0481	0.0424	0.0395
	(0.0273)	(0.0310)	(0.0280)	(0.0306)
L5tdmg_c	0.0486	0.0541	0.0365	0.0429
	(0.0348)	(0.0385)	(0.0367)	(0.0437)
Cumulative effect	0.379^{***}	0.348^{**}	0.325^{**}	0.321^{*}
	(0.114)	(0.132)	(0.105)	(0.147)
pcrealGDP	-0.00754	-0.00248	-0.00978	-0.0143
	(0.0349)	(0.0358)	(0.0359)	(0.0496)
patcount3	-0.0146	0.00350	-0.0275	-0.00144
	(0.0447)	(0.0624)	(0.0476)	(0.0617)
rd_cr_st$_{t-1}$	3.480	2.987	3.173	2.771
	(2.257)	(2.433)	(2.129)	(2.429)
t_edurdexpdf$_{t-1}$	-0.0917	-0.209	-0.0238	-0.0707
	(0.315)	(0.443)	(0.338)	(0.475)
post_97	-0.369	-0.409	-0.317	-0.340
	(0.809)	(0.798)	(0.831)	(0.965)
N	1479	1479	1479	1479
AIC	1148.3	1144.3	1153.4	1137.6
BIC	1333.8	1324.5	1365.4	1317.8
Log lik.	-539.2	-538.2	-536.7	-534.8

All regressions control for state fixed effects. State-level total number of patents is employed as the predictor of excessive zeros in ZIP and ZINB models. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C.2 Changes to the NPDWR and the SDWA

Table C.4: Changes to the SDWA and the NPDWRs

Year	Total of newly regulated	Total of revised	All contaminants	New regulation dummy	Revision dummy	SDWA Amendaments	Notes
1974	0	0	0	0	0	1	SDWA passed
1976	22	0	22	1	0	0	NPDWRs
1979	1	0	23	1	0	0	Total Trihalomethanes Rule
1986	1	1	23	0	1	1	1986 Amendments
1987	8	0	31	1	0	0	Phase I
1988	0	0	31	0	0	1	1986 Amendments: Lead Contamination Control Act
1989	4	2	35	1	1	0	Surface Water Treatment Rule and revision of total Coliform Rule
1991	28	12	62	1	1	0	Phase II and Lead and Copper, silver deletion
1992	22	1	84	1	1	0	Phase V
1995	0	0	83	0	0	0	Remand of nickel
1996	0	0	83	0	0	1	1996 Amendments
1998	7	3	90	1	1	0	Stage I Disinfectant and Disinfection Byproduct Rule Interim Enhanced Surface Water Treatment Rule
2000	1	6	91	1	1	0	Radionuclides, Lead and Copper Rule
2001	0	2	91	0	1	0	Revision: Arsenic
2002	0	2	91	0	1	0	
2005	0	0	91	0	0	1	2005 Amendments: the Energy Policy Act of 2005
2006	3	3	94	1	1	0	
2007	0	2	94	0	1	0	Revision: lead and copper
2009	0	1	94	0	1	0	Airline Drinking Water Rule
2011	0	0	94	0	0	1	2011 Amendments: the Reduction of Lead in Drinking Water Act
2013	0	2	94	0	1	0	Revised the total Coliform Rule
2015	0	0	94	0	0	1	2015 Amendments: the Drinking Water Protection Act