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Abstract

This paper examines the effect of a country's own past disaster experiences and nearby countries' past experiences on subsequent disaster damage. We use global disaster data from 1990-2010, which include disaster-related death tolls for both natural and technological disasters, that are further divided into sub-categories. Overall, we find evidence of a reduction effect of past disaster damage on future disaster damage. More detailed analyses show that an adaptation effect seems to be present for certain combinations of disaster types and levels of economic development. The results show that a country's own experiences reduce future damage for natural disasters but that the marginal effect is larger for lower-income countries. On the other hand, for technological disasters, a robust impact was found only for higher-income countries. In terms of the disaster experiences of nearby countries, which is defined by countries in the same continent, an adaptation effect was found only for natural disasters, and the marginal impact was higher for higher-income countries.

Keywords: Natural disaster, Technological disaster, Adaptation, Learning, Disaster experience, Economic development

JEL Classification: O1; Q54

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1. Introduction

Disasters are considered to be one of the major obstacles to sustainable development (United Nations International Strategy for Disaster Reduction, 2015). Disasters can be categorized as consequences of natural or technological hazards. In recent years, many countries have been the victims of different large-scale natural disasters. Earthquakes and tsunamis impacted Haiti (2010), Japan (2011), and the Philippines (2012, 2013); storms swept through the U.S. (2005), Myanmar (2008), and the Philippines (2011); heat waves hit Europe (2003) and Russia (2010); and large-scale flooding caused damages in Thailand (2011). Along with natural disasters, technological disasters with substantial damage are becoming more common. According to a report from Swiss Re, in 2015 alone, there were almost 7000 deaths from 155 incidents of technological disasters that included maritime, aviation and rail disasters, fires and explosions, mining accidents, terrorism and social unrest. Hence, both categories of disasters are important when considering ways to reduce overall disaster risks and damage.

Adaptation to natural and technological hazards by learning from past incidents plays a key role in reducing disaster risks and subsequent damage. Societies and organizations as well as the individuals within them have adjusted their behavior in response to past hazards. In addition, they are anticipating future conditions and trying to adapt to minimize disaster-related damages (Adger et al. 2005). Here, we use the concept of adaptation as measures that are taken to reduce future damages from disasters. Much of the adaptation to risks and consequences of disasters are triggered by past experiences, current events, and forecasting future events. This learning process from similar past events is a general theme of interest that is not confined to the area of disaster management.

Various studies examine the learning effect from past disasters. Drupsteen and Guldenmund (2014) provide an extensive review of the models and theories on the ‘learning from incident process’ and discuss possible obstacles that may impact the efficiency of learning, which can be used to reduce unwanted risks and damage. One of the reasons we may observe no or a small learning effect from past incidents may be partially explained by the “tendency to seek a scapegoat” in post-disaster periods. In addition, both financial and political costs as well as an organizational decision-making structure that makes reforms difficult may lower the incentive to put effort into improving disaster management (Hovden et al. 2011; Pidgeon and O’Leary 2000).

The purpose of this study is to examine whether the past disaster experiences and degree of their damage affect the damage of subsequent disasters using global disaster data, including both natural and technological disasters. We use the damage reduction effect as a representation of an adaptation effect. Our study relates to empirical studies that have used global data to provide evidence as to whether an adaptation effect exists. Kahn (2003) provided earlier empirical evidence of an adaptation effect that indicated statistically significant negative time trend of deaths per natural disaster. The case of earthquakes is a popular context in which an experience effect for natural disasters is studied. Anbarci et al. (2005) and Escaleras et al. (2007) study the impact of the propensity of major earthquakes, measured by the ratio of the number of 6+ Richter scale quakes to all earthquakes, occurring within a given country during a given period. The authors expected that a higher major earthquake propensity will improve the response to subsequent earthquakes because such a situation offers better opportunities for "learning by doing" in terms of disaster management. Two studies found different results. Using international data between 1990 and 1959, Anbarci et al. (2005) found no statistically significant impact of major earthquakes on subsequent earthquakes' death tolls.

On the other hand, Escaleras et al. (2007) used similar data to Anbarci et al. (2005) but used extended data between 1875 and 1974. They found evidence that the relative frequency of major earthquakes induces a learning effect that reduces disaster damage. Keefer et al. (2011) performed a similar analysis as Anbarci et al. (2005) and Escaleras et al. (2007) but improved the quake propensity measure to account for the exponential nature of the Richter scale and used more recent data between 1960 and 2008. They found that a relatively high frequency of major earthquakes decreases the opportunity costs of investment in earthquake mortality reduction and incentivizes political decision makers to finance reduction measures to reduce possible damages from future threats of earthquakes.

Although limited, some studies use data for natural disasters other than earthquakes. Hsiang and Narita (2012) found that countries with higher exposure to tropical cyclones have slightly lower marginal losses from storms. Similarly, Anttila-Hughes and Hsiang (2013) found that marginal damage from typhoon exposure decreases with increases in the intensity of the typhoon climate. Neumayer et al. (2014) analyzed the experience effect, measured by economic damage, for tropical cyclones and floods in addition to earthquakes.

Compared to the related literature on natural disasters, there is little empirical evidence regarding an adaptation effect for technological disasters. Coleman (2006) reported that the number of technological disasters increased exponentially but that the number of deaths due to such disasters did not change over time in the period between 1900 and 1999. With this descriptive observation, it is difficult to determine whether there is a learning effect from previous disasters.

Moreover, although a number of studies explore the impact of the disaster experiences of a country on its adaptation measures, the effect of other countries' disaster experiences remains relatively unexplored. There is some empirical evidence that policy choices in one country are influenced by the experiences and policy implementation of other countries (e.g., Brooks 2007; Elkins et al. 2006; Gilardi et al. 2009; Simmons and Elkins 2004). Hence, investments in disaster adaptation may also be affected by the experiences of others. Moreover, through the disaster experiences of other countries, especially geographically near countries where countries share similar disaster risks, governments may find it more useful to pay close attention to be informed about the possible disaster damage and effectiveness of certain disaster management policies.

Alongside discussion regarding whether disaster experiences actually induce risk and damage reductions are debate as to whether adaption capacity differs based on a country's level of economic development. UNISDR (2015) highlighted that high-income countries with strong scientific and technical communities have been able to make significant progress in monitoring and forecasting hazards risks and have developed both national and local high-quality risk assessments. On the other hand, most lower-income countries simply do not have the capacity to collect and analyze information. Kahn (2005) showed that richer countries have a negative time trend in terms of the number of disaster-related deaths, whereas poorer countries have a positive time trend, which implies successful adaption by richer countries and increased disaster damages for poorer countries. In addition, Keefer et al. (2011) found that richer countries respond more to past disaster experiences and that they have a higher reduction in death tolls than poorer countries, although a higher earthquake propensity seems to reduce mortality from subsequent earthquakes in both richer and poorer countries.

Given the implications from previous empirical studies, this paper analyzes the adaptation impact of disaster experiences, including both a country's own and nearby countries' experiences, on disaster damage. We use death tolls from past disasters as the measure of experience and study its impact on the death tolls of subsequent disasters. The scale of disaster damage can be measured by the dollar value of economic damage, which includes the property damages and monetary value of humanitarian damage from injuries and deaths; however, we use death tolls as our measure of adaptation because of the limited availability of consistent disaster-related economic damage data for various types of disasters across countries (Skidmore and Toya 2013). The disaster experiences of others influence the death reduction in a country. We create another index that includes the disaster death tolls among other countries of the same continent in order to explore the possibility of neighboring countries' disaster experiences affecting a country's disaster risk reduction.

We extend the analysis to compare the impact on natural and technological disasters, and we further analyze sub-categories of two types of disasters: nine natural disasters and three technological disasters. We also investigate whether the adaptation impact through disaster experience depends on a country's level of economic development in order to provide further empirical evidence, as previous studies have found disputing results on this topic.

Our results show that a country's own disaster experiences, regardless of whether they were natural or technological disasters, reduce death tolls of forthcoming disasters. This finding implies a robust adaptation impact of disaster experiences. In addition, other countries' disaster experiences reduce future damage in terms of disaster-related death but only for natural disasters. Furthermore, we find a statistically significant difference in the adaptation effect of natural disaster between lower-income and higher-income countries. The results show that the reduction effect of disaster experience is greater in lower-income countries than in higher-income countries.

This paper is structured as follows: Section 2 describes the empirical analysis, including the data, estimation model, and results. Section 3 discusses our results, and Section 4 concludes the paper.

2. Empirical Analysis

2-1. Data

We use the data on the annual number of deaths caused by natural and technological disasters from the Emergency Events Database (EM-DAT), which is collected by the Centre for Research on the Epidemiology of Disasters (CRED).[1] The EM-DAT has tracked 227 countries from 1900-2013. As suggested by Patt et al. (2010), data prior to 1990 may be less reliable than data collected post 1990; hence, we limit our target period to 1990-2010. The data we use for the analysis cover the natural disasters of 153 countries and technological disasters of 141 countries. Since we constructed disaster experience indices as adaption proxies using a 10-year lag of death toll data, the actual time period we analyze is from 2000-2010. Note that the data set is an unbalanced panel because some countries reported multiple disasters in the same year, whereas others reported none. If no disaster was reported in a given year, we excluded the particular country year from our data set.

[1] EM-DAT is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. CRED uses specific criteria for determining whether an event is classified as a disaster. These include 10 or more people reported killed, 100 or more people reported as affected, a state of emergency being declared, and calls for international assistance.

The EM-DAT distinguishes disasters as natural and technological disasters and divides the two disaster types into nine and three sub-categories, respectively.[2] Out of the 15 sub-categories, we used 12 disasters types for our empirical analysis: nine types of natural disasters (floods, storms, epidemics, droughts, extreme temperature events, slides, wildfires, earthquakes, and volcanic eruptions) and three types of technological disasters (transport, industrial, and miscellaneous accidents). We constructed two experience indices of a country's own experience and other countries' experience and use these two measures as proxies for adaptation. The indices are calculated using death toll data. By considering the sum of death tolls, these measures intend to capture the scale damage of past disasters.[3] Greater death tolls imply greater damage and provide greater incentives for policy makers and citizens to take proactive measures that would mitigate damages from similar future disasters.

The measure of a country's own experience, *EXP(Own),* is defined as the sum of disaster-related deaths in a given country over the past 10 years, written as follows:

$$EXP(Own)_{it} = \sum_{s=t-1}^{t-10} Death_{it}. \tag{1}$$

The index of other countries' experiences, *EXP(Others)*, is defined as all disaster-related deaths that occurred in a country's continent, excluding the death toll of a country's own experience, during the past 10 years:

$$EXP(Others)_{it} = \sum_{j=1}^{J} EXP(Own)_{jt}^{k}. \tag{2}$$

k represents 5 continental groups based on the classification used by the United Nations Statistics Division classification: Africa, the Americas, Asia, Europe, and Oceania. *J* is the set of countries within *k*, excluding country *i*.

We also use other socio-economic variables that are used as determinants of disaster damages in previous studies (Kahn 2005; Toya and Skidmore 2007; Kellenberg and Mobarak 2008). We use Version 7.1 of the Penn World Table (PWT) as the source of the following variables: GDP per capita, population, governmental share of GDP (measuring the size of government), and trade openness. The urbanization rate, defined as the percentage of a population living in an urban area, is obtained from the World Bank's World Development Indicators. We also used the polity score, an annual measurement of the degree of democracy

[2] See http://www.emdat.be/classification for a complete classification and definitions.
[3] This measure does not indicate exhaustive effects of adaptation due to data availability. Other disaster consequences, such as property losses and affected people, also influence government policy toward adaptation measures.

of a country, from the Polity IV dataset.

2-2. Estimation Model

We estimated the following fixed effects model:

$$\text{Log}(Death_{it} + 1) = \alpha + \beta_1 EXP(Own)_{it} + \beta_2 EXP(Others)_{it} + \boldsymbol{\gamma}_{\boldsymbol{n}}' \boldsymbol{X}_{\boldsymbol{it}} + \theta_t + \theta_i + \varepsilon_{it}. \quad (3)$$

Death$_{it}$ is the annual number of disaster-related fatalities in country i throughout year t.[4] The construction of *EXP(Own)*$_{it}$ and *EXP(Others)*$_{it}$ are explained in Section 2-1. $\boldsymbol{X_{it}}$ represents a vector of the socio-economic control variables and the counts of disaster events per country year, as listed in Section 2-1. θ_t is the time trend variable of the dependent variable from 2000-2010. Kahn (2003) used this time trend variable as an adaptation measure to examine whether deaths per disaster are declining over time. We also control vector country dummy variables denoted as θ_i. According to Heffernan (2012), adapting to a disaster requires extremely location-specific strategies. Hence, we also control for location-specific factors via a country's fixed effects, such as wet or dry climates, mountainous or flat landscapes, distances to the equator, and geographical proximities to seashore. Lastly, ε_{it} is the error term.

Given that the dependent variable, death tolls, is a non-negative count variable, previous studies use a negative binomial model rather than an ordinary least squares (OLS) regression model (Anbarci et al. 2005; Escaleras et al. 2007; Fankhauser and McDermott 2014; Keefer et al. 2011; Kellenberg and Mobarak 2008). However, we use an OLS regression model with fixed effects because a maximum likelihood estimation of a negative binomial model did not converge when country dummies were included. In addition, according to previous studies, the results obtained by OLS regressions and negative binominal regressions are fairly consistent with the results of the negative binomial regressions (Kellenberg and Mobarak 2008; Fankhauser and McDermott 2014).

As mentioned in the previous section, the adaptation effect may differ according to whether a country is developed or developing, but the results from previous studies are rather inconclusive. Hence, in addition, we use an income dummy, which is coded according to higher-income and lower-income countries using the World Bank classification,[5] to divide the sample and run estimation models separately. Approximately 36.6% and 37.8% of the full samples of natural disasters and technological disasters, respectively fall into the observations of the lower-

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[4] We used log(*Death*$_{it}$ + 1) as the dependent variable to avoid a loss of observations due to the number of zeros.

[5] See http://siteresources.worldbank.org/DATASTATISTICS/Resources/OGHIST.xls for the definition of income groupings.

income group (See Appendix B).

2-3. Results

Table 1 presents the estimation results for natural disasters and technological disasters. We expect that larger disaster damage experiences will have a negative impact on future disaster damages if a learning effect from previous experience exists. The coefficients of *EXP(Own)* are negative and statistically significant for all specifications. This result supports the existence of a general learning effect from a country's own past disaster experience, and the learning curve improves as past disaster damage increases. On the other hand, the coefficients of *EXP(Others)* are negative and statistically significant for natural disasters but seem to have no robust impact for technological disasters.

Table 2 shows the estimation results of separate regressions of equation (3) for the sub-categories of natural and technological types of disasters. The coefficients of *EXP(Own)* are negative and statistically significant for all sub-categories, with the exception of wildfires and volcanic eruptions. It seems that the experience effect from a country's own disaster seems to be rather robust for the broad category of disasters, supporting and extending the results of previous studies of earthquakes and limited types of natural disasters. The experiences of neighboring countries do not show a significant impact when we divide the sample into sub-categories of disaster type.

Table 3 reports the estimation results of sub-samples separated based on the level of economic development. The results show that the effect of adaptation on disaster deaths differs by the country income levels. In the case of natural disasters, lower-income countries have larger negative coefficients of *EXP(Own)* than higher-income countries. On the other hand, the negative coefficients of *EXP(Others)* are statistically significant only for higher-income countries.

In terms of technological disasters, we also find differences in the effects of *EXP(Own)* between higher-income and lower-income countries, but the situation is slightly different from the case of natural disaster. The coefficient of *EXP(Own)* in higher-income countries is negative and statistically significant, whereas that in lower-income countries is not statistically significant. The coefficients of *EXP(Others)* are not statistically significant for both samples, consistent with the results obtained by the full samples.

Figure 1 shows the predictive margins for countries' own experience for natural disasters by income level with a 95 percent confidence interval. The predictive margins are calculated from the results of models (1) and (2) in Table 3. For both lower-income and higher-income countries, higher death tolls from past disasters have highly significant and increasing marginal effects on death reductions. However, the slope of higher-income countries is flatter than that of lower-income countries, indicating the relatively greater impact of an adaptation effect on reducing mortality from natural disasters. While the marginal impact of past death tolls from natural disasters may be greater for lower-income countries, the absolute mortality in poorer countries is high compared with richer countries.

Lastly, the results of the control variables vary across specifications. In Table 1, the coefficients of GDP per capita are positive and statistically significant for natural disasters. This result is consistent with the results of Kellenberg and Mobarak (2008). The coefficients of national population are negative and statistically significant for natural disasters. Other control variables (urbanization rate, openness, size of government, and polity) are not statistically significant for all specifications. We find different results for control variables with sub-category data. In Table 2, the coefficients of the rate of urbanization and openness are positive for earthquakes. The coefficients of openness are positive for earthquakes and slides. For all specifications, polity and size of government remain statistically insignificant.

3. Discussion

3-1. Experience within a Country

The empirical results regarding the effects of a country's own experience indicate a robust reduction effect for subsequent disaster damage in terms of death tolls. In particular, the results for natural disasters are consistent with the results in previous studies (Escaleras et al. 2007; Keefer et al. 2011; Hsiang and Narita 2012). However, looking at the results more closely, we find contrasting result from the result of Keefer et al. (2011), which claimed that the reduction impact from experience effect is higher for the richer countries than poorer countries. Our results, as presented in Table 3, show that adaptation effects that reduce disaster-related deaths are greater for lower-income countries compared to higher-income countries.

One of the reasons why we may observe a greater marginal reduction effect in terms of disaster-related deaths for lower income countries is because the actual number of deaths is significantly higher for lower-income countries compared to higher-income countries, as shown in Figure 1. The relatively high death tolls can be explained by adaptation costs to take preventative measures are relatively more burdensome for poorer countries and they find it more optimal to address the aftermath rather than to take measures prior to the disasters (Anttila-Hughes and Hsiang, 2013) When these less developed and disaster-prone countries with relatively high expected death tolls experience large-scale disasters and actually take preemptive measures and invest in adaption strategies, often with financial help from developed countries and international organizations, the marginal impact of such measures is expected to be greater than the impact of additional measure taken by developed countries, which invest heavily in disaster prevention. Another possible rationale is that developed countries already have invested into prevention measures and have relatively smaller causalities for similar disaster compared to the lower-income countries, which in turn makes it increasingly harder for additional prevention measures to have large reduction impact. Hence we may observe comparatively smaller reduction effect for higher-income countries. Combination of both reasons above may explain why we observe greater marginal reduction of death tolls in poorer countries and vice versa.

In addition, while our results show that experiencing more disaster damages reduce future disaster-related deaths, in terms of the time trend of death tolls, we do not confirm significant signs of adaptation as Kahn (2003) found in his study using data between 1970-2001. This difference may be due to the difference in time period of data. Hence, we do not disprove the negative time trend of disaster related-death in his data. However, given that our data period is between 2000-2010, the results may be pointing out the change in the trend of disaster damages in recent years.

Our results also show the experience effect on the damages of technological disasters. As in the case of a natural disaster, death tolls from technological incidents decline with a country's experience of technological disasters with more damage. However, unlike in the case of natural disaster, this adaptation effect is limited to higher-income countries when analyzing the sub-samples. A possible explanation may be that the citizens, corporations and governments in developed countries take these incidents more seriously compared to less developed countries. Developed countries are likely to have higher safety technologies and more severe protocols and regulations to avoid disasters from human and technical errors. Hence, developed countries may be more sensitive to the damage of incidents and respond more comprehensively compared to the people and governments of less developed countries. This result also implies that improving the level of economic development of currently less developed countries would induce a learning effect, contributing to a decrease in the damages of technological disasters in future.

3-2. Experiences of Others

Along with the own disaster experience of a country, we also examine the diffusion effect of neighboring countries' disaster experiences. The major difference in the results between the impact of a country's own experience and other countries' experience is that whereas a country's own disaster experience has a reduction effect regardless of whether the disaster type is natural or technological, neighboring countries' disaster experiences and damages lead to a reduction in the country's disaster damage only for the case of natural disasters. We may see this varying result for different disaster types because people and governments are sensitive to the natural disaster experiences of neighboring countries given that geographically close countries are likely to share the risks of natural hazards but may not necessary share the determinants of risk for technological disasters.

Moreover, according to the results of our sub-samples divided by income level, we see the experience effect only in higher-income countries. We still did not find any statistically significant impact for technological disasters. This result may be explained by the differences in the level of adaptive capacity depending on the level of development. Smit and Pilifosova (2001) show that high-income countries have consistently higher adaptive capacity compared to lower-income countries, where the capacities are determined by the general categories of economic resources, technologies, information and skills, and qualities and coverages of infrastructure and equity. Given that countries are sensitive to disaster incidents in neighboring countries and that they take preventive measures, higher-income countries are better fit to finance such investments. Lower-income countries have low adaptive capacities; they may observe the disaster experience but may not have the capacity to invest in a disaster that has not hit them directly, regardless of the risk.

The dissemination of information and lessons is an important part of reducing damages from incurred incidents. Although globalization and international cooperation have improved media coverage and the sharing of adaption measures, we still see a limited learning effect. Hence, additional research to improve our understanding of the diffusion mechanism would be beneficial.

3-3. Future Disaster Adaptation

Our results provide several implications for future disaster adaptation strategies. In general, adaptation strategies are separated into short- and long-term strategies. Given that we use a total death tolls of 10 previous years for a given observation year as a proxy for experience, our results imply a relatively short-term learning effect from past disaster incidents. Hence, we provide two cases of successful short-term adaptations after large-scale disasters following Heffernan (2012), who indicated that the installation of warning systems is an effective short-term adaptation measure regardless of the country's level of development.

Mozambique is a disaster-prone country and was hit by a flood known to be worst in country's history, leaving 7,000 dead and damages worth US $300 million. Warnings of above-average rainfall came too late and failed to convey the magnitude of the coming flood. Soon after, the country improved the warning and monitoring systems, which increased the accuracy of rainfall prediction in terms of amount and time period. In 2007, 29 were killed instead of a few thousand, when the country was hit again by a flood with a similar magnitude as the 2000 incident.

Another example is the heat wave that hit Europe in the summer of 2003. Almost 15,000 people died in France alone, where the most extreme heat was recorded. After the 2003 disaster, France established a heatwave warning system, which eventually spread across Europe. Alerts are triggered when the five-day weather forecast predicts that temperatures will exceed thresholds for three days. When the alarm system issues public warnings, it also triggers the mobilization of personnel to visit vulnerable populations and reach hospitals and nursing-home staff to prepare for emergency needs. When a similar heat wave hit in 2006, although it did reduce the mortality rate in comparison to the 2003 incident, thousands still died because a significant fraction of the population failed to receive the warning and many did not take the warning seriously. This example shows that adaptation measures are the most effective when the government invests in and introduces technical and management systems and, more importantly, when citizens actually follow the preventive measures and take advantage of the warnings.

Our focus on the short-terms strategies does not imply that long-term adaptation strategies are less important. Decisions on urban planning, infrastructure and transportation development, large-scale construction, regulations on environmental, safety regulations and technological investment may impact the damages from disaster incidents in next few decades and even century. However, the general consensus is that it is difficult to construct and to assess the effectiveness of long-term disaster adaptation strategies where we have to predict the consequences over a much longer period. Hallegatte (2009) noted that many decisions coming with a long-term commitment are very climate sensitive, but it is difficult to predict the patterns of long term-climate change. In addition, we face larger uncertainty when we think about long-term measures. Hence, although optimal disaster management should consider the impacts in both short- and long-time frames, short-term strategies may have a more direct impact on reducing disaster damages from incidents in near future.

4. Conclusions

Although frequency and magnitude vary across countries, disasters bring damages, which often includes the most extreme damage of all, the death of people. Our empirical evidence shows that disaster experiences improve adaptation and reduce the disaster damage of subsequent disasters. The result also indicates that the larger the disaster damages, the marginal reduction effects increase. These results are rather consistent with evidence provided by previous studies.

Our study differs from previous studies in that we examine various types and sub-categories of disasters and test not only the effect of a country's own disaster experience but also the effect of neighboring countries' disasters. We find that a country's own experiences consistently impact death reductions across most disaster types, whether it is natural or technological, whereas neighboring countries' experiences matter only for natural disasters. Moreover, we find significant differences in the adaptation impact depending on the level of economic development. According to the results, the adaptation effect is stronger for lower-income countries, whereas actual average death tolls are lower in higher-income countries. For technological disasters, the adaptation effect is limited to higher-income countries. Similarly, we found that the neighbor effect for natural disasters exists only in higher-income countries. Hence, for both cases, we found that the results of the full sample were driven by the learning effect of higher-income countries.

Our results show some adaptation effect in broad categories of disasters. This may seem to be a rather encouraging result. However, the results also reveal the combinations of disaster types and country characteristics where the disaster experiences of the own country and neighboring countries have not led to learning. Moreover, as Homsma et al. (2009) claimed, 'more lessons are generated and learned from errors with severe consequences compared to similar errors with limited consequences'. At the first look, this statement seems to underline the reason for what we observe in this study; larger death tolls in previous disasters increase the reduction effect in subsequent disaster incidents. However, the other interpretation could be that we see the impact of previous damages because we use death tolls, the most severe form of damage. We may not observe a clear adaptation effect if we use other less severe damage proxies such as number of injured and displaced as well as different measures of economic damages. Thus, the adaptation effect needs to be explored further in order to deepen the understanding of how disaster experiences affect future outcomes of similar incidents.

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Table 1: Estimation Results for Natural and Technological Disasters

	Natural Disasters (2)	Technological Disasters (3)
Log (EXP(Own) + 1)	-0.343**	-0.163**
	(0.062)	(0.054)
Log (EXP(Others) + 1)	-0.223*	0.096
	(0.101)	(0.278)
Log (GDP per capita)	1.272*	0.165
	(0.500)	(0.320)
Log (National Population)	-4.126**	-0.771
	(1.394)	(0.952)
Urbanization Rate	0.054	-0.042
	(0.041)	(0.024)
Openness	-0.006	0.003
	(0.004)	(0.003)
Size of Government	0.001	0.006
	(0.027)	(0.015)
Polity	0.050	-0.002
	(0.028)	(0.013)
Time Trend	0.047	0.038
	(0.033)	(0.020)
Log (No. of Floods + 1)	0.379**	
	(0.109)	
Log (No. of Storms + 1)	0.459**	
	(0.133)	
Log (No. of Epidemics + 1)	1.254**	
	(0.135)	
Log (No. of Extreme Temperature Events + 1)	1.901**	
	(0.255)	
Log (No. of Droughts + 1)	-0.420*	
	(0.195)	
Log (No. of Slides + 1)	0.741**	
	(0.226)	
Log (No. of Wildfires + 1)	0.845**	
	(0.197)	
Log (No. of Earthquakes + 1)	0.538*	
	(0.247)	
Log (No. of Volcanic Eruptions + 1)	0.259	
	(0.313)	
Log (No. of Industrial Accidents + 1)		1.257**
		(0.081)
Log (No. of Miscellaneous Accidents + 1)		0.516**
		(0.079)
Log (No. of Transportation Accidents + 1)		0.336**
		(0.097)
Constant	33.019*	10.507
	(14.579)	(9.170)
Country Fixed Effects	Yes	Yes
No. of Observations	1,204	820
No. of Countries	153	141
Adj. R-Squared	0.597	0.702

Note: * Significant at 5% level, ** Significant at 1% level. The numbers in parentheses are robust standard errors. The dependent variable is log(death + 1).

Table 2: Estimation Results for each type of Disaster

	Flood (1)	Storm (2)	Epidemic (3)	Extreme Temperature (4)	Drought (5)	Slide (6)	Wildfire (7)	Earthquake (8)	Volcanic Eruption (9)	Transport Accident (10)	Miscellaneous Accident (11)	Industrial Accident (12)
Log (EXP(Own) + 1)	-0.275**	-0.202*	-0.479**	-0.589**	-0.454*	-0.345*	-0.168	-0.396*	-0.149	-0.175**	-0.300**	-0.333**
	(0.064)	(0.091)	(0.081)	(0.108)	(0.186)	(0.161)	(0.358)	(0.190)	(0.213)	(0.044)	(0.092)	(0.098)
Log (EXP(Others) + 1)	-0.199	-0.007	0.384	-0.296	-0.020	-0.604*	0.057	-0.622	0.323	0.074	-0.311	0.313
	(0.178)	(0.145)	(0.381)	(0.170)	(0.211)	(0.255)	(0.408)	(0.437)	(0.358)	(0.236)	(0.428)	(0.421)
Log (GDP per capita)	-0.674	-1.077	1.907	8.692**	-0.802	2.000	10.139	4.029	20.275*	0.115	0.097	-0.937
	(0.580)	(0.876)	(1.039)	(2.329)	(1.567)	(2.378)	(6.794)	(3.031)	(7.227)	(0.267)	(0.767)	(1.009)
Log (National Population)	0.091	3.798	-8.499**	-9.391	-4.131	15.842*	14.673	18.698	17.792	0.603	-2.378	0.273
	(1.521)	(2.509)	(3.225)	(6.280)	(3.523)	(6.692)	(15.349)	(10.258)	(26.313)	(0.871)	(2.789)	(3.759)
Urbanization Rate	0.039	0.072	-0.029	-0.003	-0.009	0.230	-0.457	0.410**	0.117	-0.033	-0.062	-0.037
	(0.039)	(0.052)	(0.118)	(0.209)	(0.084)	(0.125)	(0.450)	(0.140)	(0.194)	(0.018)	(0.088)	(0.064)
Openness	-0.003	0.017	-0.003	-0.027	0.003	0.022*	0.016	0.050*	-0.009	-0.001	0.002	0.019
	(0.005)	(0.009)	(0.008)	(0.023)	(0.007)	(0.010)	(0.034)	(0.021)	(0.058)	(0.002)	(0.008)	(0.010)
Size of Government	-0.000	0.040	-0.001	0.116	0.056	-0.055	0.308	0.269	0.863	-0.008	-0.024	0.002
	(0.034)	(0.084)	(0.047)	(0.198)	(0.136)	(0.087)	(0.520)	(0.188)	(0.565)	(0.011)	(0.059)	(0.061)
Polity	-0.053	0.043	0.094	-0.018	-0.097	0.033	-0.173	0.051	-0.033	-0.000	0.005	-0.205
	(0.033)	(0.065)	(0.055)	(0.061)	(0.110)	(0.078)	(0.435)	(0.170)	(0.228)	(0.011)	(0.029)	(0.112)
Log (No. of Disaster Events + 1)	1.442**	1.439**	1.940**	1.156	-2.372	2.172**	0.014	3.253**	2.542*	1.608**	1.800**	1.543**
	(0.170)	(0.278)	(0.308)	(0.946)	(2.171)	(0.316)	(0.709)	(0.922)	(1.059)	(0.082)	(0.277)	(0.305)
Time Trend	0.047	-0.049	0.219*	-0.0218	0.011	-0.518**	-0.113	-0.402	-0.763	0.010	0.152*	0.143*
	(0.037)	(0.039)	(0.107)	(0.114)	(0.057)	(0.166)	(0.195)	(0.223)	(0.557)	(0.021)	(0.066)	(0.064)
Constant	6.827	-33.088	69.507*	26.374	49.268	-191.86*	-217.82	-254.84*	-364.86	-2.983	32.186	6.136
	(16.883)	(26.908)	(32.304)	(67.714)	(35.469)	(80.913)	(193.05)	(127.04)	(272.10)	(8.210)	(29.207)	(43.982)
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Observations	843	435	372	204	174	135	100	161	45	722	287	180
Adj. R-Squared	0.569	0.607	0.523	0.526	0.244	0.467	0.237	0.409	0.303	0.719	0.419	0.668
No. of Countries	133	112	106	60	82	49	43	60	18	133	93	63

Note: * Significant at 5% level, ** Significant at 1% level. The numbers in parentheses are robust standard errors. The dependent variable is log(*death* + 1).

Table 3: Interaction between Adaptation Measures and Poor Measures

	Natural Disasters		Technological Disasters	
	Lower-income	Higher-income	Lower-income	Higher-income
	(1)	(2)	(3)	(4)
Log (EXP(Own) + 1)	-0.466**	-0.358**	-0.128	-0.212**
	(0.150)	(0.073)	(0.079)	(0.080)
Log (EXP(Others) + 1)	-0.290	-0.266*	-0.465	0.301
	(0.417)	(0.106)	(0.555)	(0.417)
Log (GDP per capita)	0.749	2.181**	-0.187	0.589
	(0.812)	(0.782)	(0.560)	(0.450)
Log (National Population)	-4.082	-1.954	-1.714	-0.581
	(3.619)	(2.582)	(2.023)	(1.149)
Urbanization Rate	0.130	-0.022	-0.056	-0.055
	(0.089)	(0.044)	(0.048)	(0.034)
Openness	-0.002	-0.001	0.004	0.003
	(0.005)	(0.007)	(0.004)	(0.005)
Size of government	0.020	0.008	-0.008	0.037
	(0.033)	(0.074)	(0.018)	(0.032)
Polity	0.046	0.012	-0.002	-0.004
	(0.036)	(0.053)	(0.017)	(0.027)
time2000	0.011	0.029	0.098	0.032
	(0.099)	(0.044)	(0.057)	(0.027)
Country Fixed Effects	Yes	Yes	Yes	Yes
No. of Observations	441	763	310	510
No. of Countries	61	118	55	102
Adj. R-Squared	0.600	0.590	0.731	0.683

Note: * Significant at 5% level, ** Significant at 1% level. The numbers in parentheses are robust standard errors. The dependent variable is log(death + 1). Independent variables not reported in the table are the number of each type of disaster, and the constant.

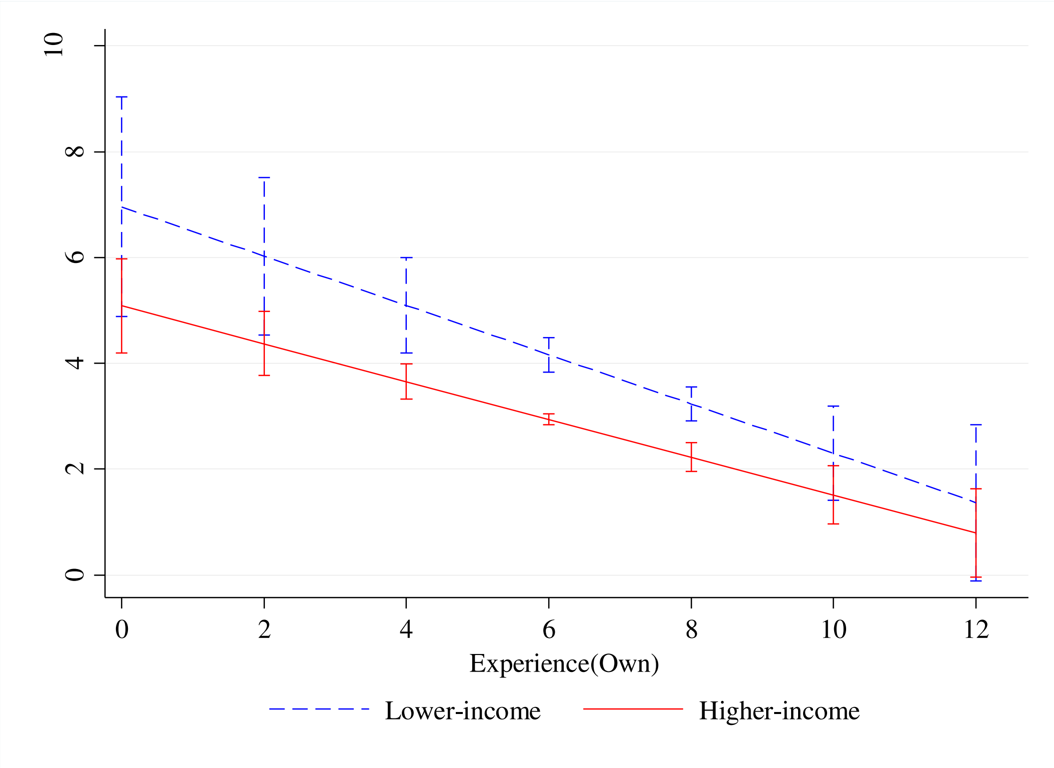

Figure 1: Predictive margins of higher- and lower-income countries' own experiences of natural disasters with 95% CI.

Appendix A

Table A-1: List of Countries in the Samples

Afghanistan	Ecuador	Lebanon	Senegal
Albania	Egypt	Lesotho	Serbia*
Algeria	El Salvador	Liberia*	Sierra Leone
Angola	Equatorial Guinea	Libyan Arab Jamah**	Singapore*
Argentina	Eritrea	Lithuania	Slovakia
Armenia	Estonia	Macau	Slovenia
Australia	Ethiopia	Madagascar	Solomon Is*
Austria	Fiji*	Malawi	Somalia
Azerbaijan	Finland	Malaysia	South Africa
Bahrain**	France	Mali	Spain
Bangladesh	Gabon	Mauritania	Sri Lanka
Belarus	Gambia The	Mauritius*	Sudan
Belgium	Georgia	Mexico	Suriname
Benin	Germany	Moldova Rep*	Swaziland
Bhutan*	Ghana	Mongolia	Sweden*
Bolivia	Greece	Montenegro*	Switzerland
Botswana*	Guatemala	Morocco	Syrian Arab Rep
Brazil	Guinea	Mozambique	Tajikistan
Bulgaria	Guinea Bissau	Namibia	Tanzania Uni Rep
Burkina Faso	Guyana*	Nepal	Thailand
Burundi	Haiti	Netherlands	Togo
Cambodia	Honduras	New Zealand	Trinidad and Tobago
Cameroon	Hungary	Nicaragua	Tunisia
Canada	India	Niger	Turkey*
Cape Verde Is	Indonesia	Nigeria	Turkmenistan*
Central African Rep	Iran Islam Rep	Norway	Uganda
Chad	Iraq**	Oman	Ukraine
Chile	Ireland*	Pakistan	United Arab Emirates**
China P Rep	Israel	Panama	United Kingdom
Colombia	Italy	Papua New Guinea	United States
Comoros	Jamaica*	Paraguay	Uruguay
Congo	Japan	Peru	Uzbekistan
Costa Rica	Jordan	Philippines	Venezuela
Cote d'Ivoire	Kazakhstan	Poland	Viet Nam
Croatia	Kenya	Portugal	Yemen
Cuba	Korea Rep	Qatar**	Zaire/Congo Dem Rep
Cyprus	Kuwait	Romania	Zambia
Denmark	Kyrgyzstan	Russia	Zimbabwe
Djibouti	Lao P Dem Rep	Rwanda	
Dominican Rep	Latvia	Saudi Arabia	

* indicates the samples for natural disasters. ** indicates the samples for technological crises.

Appendix B

Table B-1: Descriptive Statistics

Variable	Natural Disasters Mean	Natural Disasters Std. Dev.	Technological Disasters Mean	Technological Disasters Std. Dev.
Log (Annual Deaths + 1)	3.224	2.242	3.926	1.326
Log (EXP(Own) + 1)	6.348	2.347	5.856	1.777
Log (EXP(Others) + 1)	11.218	1.249	9.918	0.822
Log (GDP per capita)	8.315	1.336	8.285	1.338
Log (National Population)	9.625	1.485	10.038	1.477
Urbanization Rate: %	51.836	22.319	52.663	22.328
Polity: -10 – 10	4.209	5.744	3.139	6.115
Openness: %	75.826	38.566	69.714	34.281
Size of Government: %	10.322	6.102	9.629	5.345
Log (No. of Floods + 1)	0.718	0.591		
Log (No. of Storms + 1)	0.372	0.579		
Log (No. of Epidemics + 1)	0.279	0.457		
Log (No. of Extreme Temperature Events + 1)	0.127	0.288		
Log (No. of Droughts + 1)	0.103	0.255		
Log (No. of Earthquakes + 1)	0.123	0.344		
Log (No. of Slides + 1)	0.099	0.299		
Log (No. of Wildfires + 1)	0.069	0.246		
Log (No. of Volcanic Eruptions + 1)	0.030	0.160		
Log (No. of Transportation Accidents + 1)			1.046	0.678
Log (No. of Miscellaneous Accidents + 1)			0.319	0.489
Log (No. of Industrial Accidents + 1)			0.216	0.519
Observations	1,204		820	
Proportion of Lower-income Countries: %	36.6		37.8	