

# The Political Economy of Natural Disaster Damage

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# The Political Economy of Natural Disaster Damage

## Abstract

Economic damage from natural hazards can sometimes be prevented and always mitigated. However, private individuals tend to underinvest in such measures due to problems of collective action, information asymmetry and myopic behavior. Governments, which can in principle correct these market failures, themselves face incentives to underinvest in costly disaster prevention policies and damage mitigation regulations. Yet, disaster damage varies greatly across countries. We argue that rational actors will invest more in trying to prevent and mitigate damage the larger a country's propensity to experience frequent and strong natural hazards. Accordingly, economic loss from an actually occurring disaster will be smaller the larger a country's disaster propensity – holding everything else equal, such as hazard magnitude, the country's total wealth and per capita income. At the same time, damage is not entirely preventable and smaller losses tend to be random. Disaster propensity will therefore have a larger marginal effect on larger predicted damages than on smaller ones. We employ quantile regression analysis in a global sample to test these predictions, focusing on the three disaster types causing the vast majority of damage worldwide: earthquakes, floods and tropical cyclones.

## 1. Introduction

With an estimated economic loss of between 82 billion (Knapp et al. 2005), 125 billion (Munich Re 2011) and 150 billion US\$ (Burton and Hicks 2005), hurricane Katrina used to be the costliest natural disaster ever. Then March 2011 came and with it the earthquake and subsequent tsunami in Japan. Estimated costs of this disaster have grown over time to 235 billion (World Bank, March 21) and finally to 309 billion US\$ according to economic and fiscal policy minister Kaoru Yosano (Xinhua, March 23). Whatever the final cost will be, the Tōhoku quake will prove to be the most expensive natural disaster of all time.

Should it be surprising that the two costliest disasters were triggered by a hurricane in the US and an earthquake in Japan? On one level, the answer is clearly no. Common sense tells us that economic damage of natural disasters is higher the wealthier the affected country and the US and Japan are among the wealthiest nations in the world, though hurricane Katrina and the Tōhoku quake struck relatively poor areas of these countries.

Still, we argue in this article that because the US and Japan are frequently hit by strong tropical cyclones and quakes, the predicted resulting economic loss is *systematically lower* than if cyclones and quakes of similar magnitude struck countries where such natural hazards generally tend to be less frequent and less strong. Natural disaster propensity, i.e. the frequency and intensity of experiencing natural hazards of a certain type, influences disaster damage because it determines the incentives faced by governments and private actors in undertaking measures that will prevent or at least mitigate damage in case hazard strikes. In this respect, the two costliest disasters in human history are outliers. They were so costly because existing safety measures were insufficient and failed, not because the US and Japanese governments irration-

ally abstained from taking any precautionary measures in the face of high tropical cyclone and earthquake propensity, respectively. In fact, a safety device that fails leads to the worst case scenario: If individuals rely on the functioning of, say, a dam they will accumulate more wealth in areas behind the dam than they would have in the absence of the dam, thereby exacerbating the disaster effects (Hallegatte 2012). Thus, the absence of security measures reduces the cost of the worst disasters but increases the cost of the average disaster.

In Keefer et al. (2011), we developed a theoretical argument predicting that earthquake propensity reduces earthquake mortality. Here, we augment our analysis in two important ways. First, we move the focus of the analysis from the death toll of disasters to the economic toll. While there is a growing literature analyzing the determinants of disaster mortality (e.g., Kahn 2005; Anbarci et al. 2005; Escaleras et al. 2007; Neumayer and Plümper 2007; Plümper and Neumayer 2009, Keefer et al. 2011) as well as a nascent literature on the determinants of disaster damage (e.g. Mendelsohn and Saher 2011; Schumacher and Strobl 2011) we are the first to argue that the political economy of natural disaster damage predicts systematically lower damage for any given disaster in high disaster propensity countries.

Whether the effect of disaster propensity on mortality carries over to economic damage is not clear *a priori*. For example, early warning systems, which can dramatically reduce fatality for some disaster types if people are moved out of harm's way in time, are less effective for preventing economic loss as buildings and infrastructure cannot be entirely moved out of harms way before hazards strike. One consequence is that there are many more disaster events with recorded economic loss than with recorded loss of life. While previous studies had to rely on publicly available datasets, which do not report damage estimates for most events, we can employ data from a

comprehensive database assembled by Munich Re, the biggest re-insurance company in the world.

Second, we extend the analysis to other types of natural disasters, demonstrating that the systematic impact of disaster propensity is not restricted to earthquakes, but carries over to the other two major disaster types, tropical cyclones and floods. Together with earthquakes, they account for roughly 70 percent of total worldwide economic damage from natural disasters.

In the next section, we develop a political economy theory of natural disaster prevention and loss mitigation. We discuss the various reasons why private individuals underinvest in such measures. Governments can step in to overcome collective action, information asymmetry and myopic behavior problems, but they also suffer from similar incentives to underprovide disaster prevention and loss mitigation measures. We argue that private and public incentives are a function of disaster propensity (the expected frequency and magnitude with which hazards strike). In section 3, we describe our empirical research design in some detail and report results in section 4 from our empirical analysis. Section 5 conducts two important sets of robustness tests. Section 6 concludes.

## **2. Natural Disaster Prevention and Damage Mitigation**

Modern science has identified the causes of natural hazards and how to prevent or mitigate their consequences. Hazards are events triggered by natural forces, but they only turn into disasters if people are exposed to the hazard and are not resilient to fully absorbing the impact without damage to life or property (Schwab et al. 2007; Paul 2011).

Three major, commonly accepted, factors determine disaster damage. First and foremost, the size of economic loss depends on the magnitude of the natural hazard

event triggering the disaster. All other things equal, a stronger earthquake, for example, will cause more damage than a more moderate one and below a certain threshold a quake can hardly be felt, let alone cause much damage. Second, the economic toll is higher the wealthier the area hit by the natural hazard (Pielke et al. 1999; Neumayer and Barthel 2012; Bouwer 2011). While human beings cannot prevent natural hazards or reduce their strengths, they massively influence the level of wealth exposed to the forces of nature. There is also a risk that anthropogenic greenhouse gas emissions might increase the occurrence or the strength of weather-related natural hazard events (Min et al. 2011; Pall et al. 2011). Of course, the likely geographic location of disasters is more easily predictable for some disaster types (e.g., volcanoes) than others (e.g., earthquakes) and for some hardly at all (e.g., hail storm). However, people accumulate wealth in areas known to be prone to, say, flooding or hurricane landfall or known to be near active tectonic plate boundaries. And third, people can either entirely prevent damage with appropriate protection measures or at least mitigate damage by increasing the resistance of the exposed wealth stock to the hazard impact. Better constructed buildings and infrastructure, even if they were not explicitly built with natural hazards in mind, can more easily withstand ground shaking and high-speed winds, for example, than more poorly constructed ones.

A theory of disaster damage, however, has to go beyond this functionalist logic and also explain why some private individuals and governments specifically invest in disaster prevention and damage mitigation while others do not or not as much. We argue that investment incentives depend on the probability and expected magnitude of natural hazards, what we call disaster propensity. Where propensity is high, individuals have higher incentives to privately invest in prevention and mitigation measures and policy-makers are more likely to enact and enforce such measures than where

propensity is low. We start with private individuals (both households and profit-maximizing firms). We argue that due to market failures and due to the expectation of public transfers after disaster, private individuals tend to underinvest in disaster prevention and damage mitigation, even if disaster propensity is large, but more so when it is low. We then turn to governments, which can intervene to correct these market failures. Unfortunately, government intervention and investment in disaster prevention and mitigation might induce individuals in turn to lower their own investments.

### *2.1 Private Underinvestment in Disaster Prevention and Loss Mitigation*

Private individuals can adopt two main strategies for reducing expected disaster costs. They can refrain from settling or economically operating in high-risk areas or they can construct buildings and infrastructure in a way as to minimize the probability that they will become damaged if and when a hazard strikes. Neither strategy is particularly popular. High-risk areas such as coastlines or flood plains are often places that provide large economic and amenity values to those settling or operating there – so long as nothing happens. Strong natural hazards tend to be rare, and the time of their occurrence as well as their exact location essentially unpredictable, prompting individuals to neglect or ignore the risk. For example, no one knows when exactly an earthquake will strike or with what magnitude or where its epicenter will be (Hough 2010).

The second strategy is costly and thus unpopular, too. Earthquake-proof constructions increase building costs by at least 10 percent (Kenny 2009), solidly constructed dwellings that can withstand high top wind speeds are more expensive than light-weight wood constructions that can easily be blown away, and so on. Individual solutions to floods are even more expensive, which is why the Dutch water boards, some of which stem from the 13<sup>th</sup> century, can be regarded as one of the earliest publicly provided goods. Compared to the opportunity cost of not settling or operating in

high-risk areas, the costs of disaster-proofing settlements are typically smaller. Yet, individuals often ignore potential impacts that come with very small probability, unknown size and unknown timing (Camerer and Kunreuther 1989; Kunreuther 1996) and therefore fail to sufficiently protect their property against natural hazards.

Even if individuals are willing to invest in disaster-proofing buildings, they face the additional uncertainty that whether a building will in fact be able to withstand the full force of a natural hazard is unknown even to the owner. It is exacting on the prospective owner to supervise the construction process in order to verify the quality of the materials used and of the construction itself, while disaster-proofness is difficult to verify after construction. These information asymmetries generate disincentives for voluntary private investment in disaster-proof construction. As Akerlof (1970) has argued, an information gap between seller and buyer leads to a situation in which sellers do not sell high quality products and buyers assume that goods sold on this market are of low standard. Applied to the disaster-proofness of buildings (Anbarci et al. 2005), this means investors will find it difficult to get a higher price for high-quality disaster-proof constructions, which in turn discourages investment in such constructions in the first place.

To make things worse, even constructors do not fully know the exact hazard strength up to which a construction can withstand the hazard's destructive force. For those constructing a building and willing to invest in disaster-proofness, the worst case scenario is to invest marginally too little, in which case the costs of construction rise, but the building still does not withstand the hazard if it occurs. To be on the safe side, investors would thus have to invest significantly more than the highest expected level of hazard strength requires. This renders the investment even more expensive than on average necessary.



Another reason why private actors tend to underinvest in disaster prevention and damage mitigation is that they can cover themselves against the low-probability risk of natural disaster loss by purchasing insurance. Certain disaster types will be covered by general insurance policies, for others individuals or businesses need to buy special policies. However, sometimes insurance companies outright refuse to sell specific insurance policies in particularly high risk areas or set premia so high that few wish to buy them. Even if private individuals buy insurance, this does not reduce the total economic toll of natural disasters, unless the insurance policies are tied to certain requirements that can prevent or mitigate natural disaster loss and that the insured need to demonstrate to have enacted in order to receive pay-out. Often, the exact opposite may be the case: insured individuals exert less effort at pre-emptively reducing natural disaster loss in the knowledge that they will be insured in the event the hazard strikes – a phenomenon well-known as moral hazard. A similar problem arises if governments compensate disaster victims for their losses. In fact, governments amplify the moral hazard problem by creating a so-called charity hazard problem (Raschky and Weck-Hannemann 2007).

Also, buildings and infrastructure can be made to resist the forces of some types of natural hazards such as earthquakes and hurricanes, but not others. It would be prohibitively expensive for individuals to build flood-proof or fire-proof constructions. No construction can withstand the lava flow from the eruption of a volcano. For these disaster types, either individuals resist the temptation to settle and economically operate in high-risk areas, which as argued above is unlikely, or the government needs to step in with regulations and other policies preventing or reducing settlement or organizing joint and collective investments such as dykes or flood management schemes

protecting buildings and infrastructure that cannot be rendered disaster-proof individually.

Finally, private individuals will underinvest in disaster prevention and mitigation policies because some of the economic damage in the form of indirect losses will be felt not by individuals directly affected, but by others in the wider sub-national region or even the entire country. Large-scale disasters cause significant collateral damage and macroeconomic distortions that impact the wider population (Lall and Deichmann 2010; Hallegatte and Przyluski 2011). Only governments can internalize these costs that private individuals will ignore and we now turn to the role of public policy.

## *2.2 Underprovision of Public Disaster Prevention and Damage Mitigation Policies*

Governments exert a strong influence on disaster costs. To start with, many buildings and the vast majority of a country's infrastructure such as roads, ports, airports, power lines etc. are built for public ownership, in full or in part. Governments can thus directly impact the quality of these constructions. But the influence of governments reaches much further (Paul 2011). With private investment into disaster prevention and loss mitigation riddled by market failures caused by collective action problems, information asymmetries and myopic behavior of economic actors, governments could step in to correct these failures. They can discourage or even ban settlement or business operations in particularly high-risk areas. They can pass and strictly enforce disaster-proof building standards (Kenny 2009; World Bank and United Nations 2010). They can overcome the collective action problem and provide public goods in the form of dam constructions, flood management and warning schemes (Carsell et al. 2004), fire fighting facilities and the like.

Not unlike their citizens, however, governments have incentives to underinvest in such policies. They face the following dilemma. On the one hand, they can engage in transfer payments for the benefit of pivotal groups with political influence or in projects which promise to increase short-term political support, but are entirely irrelevant for preventing or mitigating disaster damage. On the other hand, they can invest in prevention and mitigation measures, which will only increase political support in the relatively unlikely event of a severe disaster and is costly both in terms of direct and opportunity costs. Not surprisingly, many governments prefer short-term political support. This is consistent with the findings of Gasper and Reeves (2011) who show that citizens pay greater attention to post-disaster policies than to pre-disaster prevention and mitigation measures. Governments, though they perfectly know that a certain amount of long-term investments in disaster prevention and mitigation is in the social interest, decide in favor of their short-term incentives and invest too little. Illustrative of such incentives is that no one seems to have followed the example of the mayor of the small city of Fudai on the North-East coast of Japan who in the 1960s built a sixteen meter high concrete wall against tsunami waves, which protected Fudai's 3000 inhabitants from the tsunami waves following the March 2011 earthquake. In his days, mayor Wamura was accused of and ridiculed for wasting public money, even though the construction was greatly facilitated by mountains on both sides of the dam such that the construction merely needed to close a gap between mountains (Daily Mail 2011). Other villages in the vicinity built much smaller dams, which were simply washed over by the March 2011 tsunami.

Likewise, in the knowledge that discouraging or banning settlement and business operations in high-risk areas is politically unpopular unless a natural disaster occurs, governments will under-engage in such policies. The same applies for passing

and enforcing building standards (Healy and Malhotra 2009), which will be perceived as an additional burden on private individuals that serves little purpose in the absence of disaster. Yet, governments clearly vary in the extent to which they invest in prevention and mitigation measures and our aim is to understand why.

We argue that these incentives are largely influenced by the likelihood and expected strength of potential future hazard events. Though neither probability nor magnitude can be known with certainty, areas differ in their propensity to experience frequent and strong natural hazards. For simplicity, we call this disaster propensity even though it is strictly speaking hazard propensity or the propensity to experience *potential* disasters that matters. Disaster propensity can be approximately known by governments and the public either via receiving expert advice from scientists or simply by inference from a country's past history of events. Disaster propensity in turn also affects tax-payers' willingness to pay for costly prevention and mitigation measures implemented by the government. Thus, the degree to which a government loses political support from voters and organized interests depends on whether citizens perceive such measures as responsible government action or wasteful over-reaction. Governments that invest more than citizens are willing to accept lose support. Loss of support amongst citizens is more important for democratic countries than for autocracies, in which the support amongst a small ruling elite matters more. However, even autocracies cannot entirely ignore citizen support and in Keefer et al. (2011) we explore the conditioning effect of political regime type and other governance aspects on earthquake mortality. We leave an exploration of such heterogeneity across political regimes in their response to natural hazard risk to future research.

In sum, when the expected damage of a potential disaster increases, governments are incentivized to invest more in disaster prevention and damage mitigation.

Put differently, a high disaster propensity lowers the political costs to governments of investing in prevention and mitigation measures, while a low disaster propensity increases these costs. Governments in countries with a high disaster propensity will thus invest more in such policies than governments in countries with a low disaster propensity.

Does this mean that governments in high propensity countries can entirely prevent disaster damage? This is unlikely to be the case for most hazards. Quake-proofing buildings, for example, can avert their collapse, but cannot entirely prevent property damage within buildings from the shaking of the ground transmitted into the shaking of buildings. Infrastructure and buildings that withstand collapse may still be damaged as the quake causes cracks and other deficiencies that require repair. Worse still, earthquakes can also trigger tsunamis, landslides and fires, which are much more difficult to mitigate, let alone prevent. It is telling that a significant portion of the damage of Japan's two costliest earthquakes – the 1995 Kobe quake and the 2011 Tōhoku quake – was caused not by the ground shaking itself, but by the ensuing fire and tsunami waves, respectively. Likewise, better constructed buildings and infrastructure can escape collapse from very high wind speeds, but windows may still be smashed if a tropical cyclone passes through. Some damage will be caused by debris dragged along by the storm, while the associated rainfall may cause local flooding. In the worst case scenario (e.g. hurricane Katrina), the strong winds cause a storm surge that breaks the protective dam system. Flood damage can more easily be entirely prevented with a proper system of dams and dykes in place. But it is very difficult to prevent local flooding damage everywhere altogether. Such damage can occur because the rainfall in an area exceeds the intake capacity of the ground and, where existent,

of the drainage system or because strong rainfall lets creeks and rivers swell and eventually leave their streambed where dams and dykes are not existent or are inadequate.

Two conclusions follow from our reasoning. First, policies enacted by governments in high disaster propensity countries typically cannot fully prevent natural disaster damage. Small-scale damage is often unavoidable and essentially random. For example, the average estimated damage of minor earthquakes – smaller than 6.0 on the Richter scale – in the low quake propensity countries of Spain (.19 million US\$), Germany (10.6 million US\$) and the UK (16.2 million US\$) varies for no apparent reason and is not much different from the average damage of 3.9 million US\$ caused by minor quakes in Japan with its extreme quake propensity (all values deflated to 2009 prices). Where disaster preparedness should have its strongest effect is in the mitigation and prevention of large-scale damage. Japan is plagued by frequent large quakes. Yet only eleven quakes over the period 1980 to 2009 inflicted damage in excess of 500 million US\$, only five in excess of one billion US\$ and only two in excess of 30 billion US\$. Compare this to Italy with its much lower quake propensity, where a rare earthquake of magnitude 6.3 on the Richter scale struck close to the town of L'Aquila in Central Italy in April 2009, leaving almost 300 people dead and causing an estimated damage of 2.5 billion US\$. In contrast, the worst damage any quake of magnitude 6.3 (or lower) ever caused in Japan was 586 million US\$.

The second conclusion following from our reasoning is that while governments in high disaster propensity countries have an incentive to enact policies that can mitigate large-scale damage for most of the time, they also have a higher likelihood of experiencing an outlier disaster event with extreme damage. Exactly because high disaster propensity means that the country is frequently hit by strong natural hazards, the likelihood increases that one of these events exceeds the disaster preparedness ca-

capacity that otherwise prevents large-scale damage. Hurricane Katrina caused damage that is about four times larger than the next most damaging hurricane during the 1980 to 2011 period and at least one order of magnitude larger than average damage for similarly strong tropical cyclones. The 1995 Kobe quake and the 2011 Tōhoku quake caused about three and ten times higher damage, respectively, than the third most damaging quake from 2004 in Chūetsu as well as damage far in excess of average damage for even large Japanese quakes. Largely reduced damage from strong disaster events can thus go hand in hand with extreme damage from extreme outlier events.

### **3. Research Design**

In this section, we test the hypothesis that follows from our discussion of the political economy of natural disaster damage, namely that countries with higher disaster propensity experience lower damage for a hazard of any given strength and that the effect of disaster propensity is more pronounced at the upper end of the disaster damage distribution. This renders ordinary least squares (OLS), the standard workhorse of econometric analysis, ill-suited for two reasons. First, it is vulnerable to the existence of outliers, which as argued above are bound to exist. Second, it fails to take into account that disaster propensity is likely to have stronger effects at the top end of the conditional disaster damage distribution than at its lower end. In contrast, quantile regression, our chosen estimation technique, is more robust to the presence of outliers and allows us to go “beyond models for the conditional mean” (Koenker and Hallock 2001: 151) by estimating different effects of the explanatory variables at different points of the conditional disaster damage distribution, thus providing a fuller picture of the impact of the explanatory variables than just the conditional mean given by OLS. It is also more suitable for heteroskedastic data (Cameron and Trivedi 2009:

205) and inspection of residuals as well as formal tests suggest the presence of heteroskedasticity in our data.

We use quantile regression with bootstrapped standard errors with 100 sampling repetitions. We report detailed results for five quantiles, namely the .05, .25, .5 (median), .75 and .95 quantiles, but for the effect of disaster propensity we also present graphs, which show its changing effect as one continuously moves in .05 intervals from the .05 to the .95 quantile. A quantile (or percentile)  $q$  is defined such that  $q$  proportions of the values of the dependent variable fall below and  $(1-q)$  proportions fall above. Quantile regression works similarly to OLS. The estimation formulas are somewhat complex involving linear programming techniques (Cameron and Trivedi 2009: 206-207), but in essence rather than minimizing the sum of squared residuals as with OLS, one minimizes the sum of equally weighted absolute residuals for the median quantile and the sum of asymmetrically weighted absolute residuals for all other quantiles (Koenker and Hallock 2005: 145).

Analysis of disaster damage is hampered by the fact that none of the publicly available disaster datasets provide comprehensive economic loss estimates. This paper's analysis benefits from the authors having been granted access to a unique high-quality dataset compiled by Munich Re (2011), the biggest re-insurance company in the world. The construction and maintenance of the dataset is described in detail in Wirtz et al. (2012) and Kron et al. (2012). Economic loss consists predominantly of damage to buildings and the physical infrastructure, but also of production losses if economic operations are interrupted as a result of the disaster. Even price increases as a consequence of demand surges in the wake of large disasters are included. What is not included, however, is the loss of life and no measures of the statistical value of life lost enters the economic damage estimates.



The data are of course not perfect. For example, smaller disasters are underreported especially in the early periods. Likewise, data on disasters in developing countries appear to be less reliable than data on events in developed countries. Still, with more than 20,000 entries of country years with recorded disaster damage over the period 1980 to 2009, it is by far the most comprehensive existing global database on natural disaster damage. The database reaches further back in time, but Munich Re acknowledges that before 1980 the data become increasingly unreliable and incomplete.

In order to maintain the database, several analysts gather information about natural disaster events. Information on economic losses is collected from a variety of sources including government representatives, relief organizations and research facilities, but also based on information of insurance associations and insurance services as well as on claims made by Munich Re's customers. Initial reports on losses, which are usually available in the immediate aftermath of a disaster, are often highly unreliable. To deal with these problems, data are updated continuously as more accurate information becomes available, which might be even years after the disaster event.

Munich Re groups natural disasters into one of 24 types. These are avalanche, blizzard/snow storm, drought, flash flood, cold wave/frost, general flood, ground shaking/earthquake, hail storm, heat wave, lightning, landslide, local windstorm, sandstorm, storm surge, subsidence, tropical cyclone, tempest/severe storm, tornado, tsunami, rockfall, volcano, winter damage, wildfire, winter storm. We study the three types that cause the largest economic damage: earthquakes, tropical cyclones and general floods. General floods are distinguished from and do not include flash floods, storm surges and tsunami flooding (Kron et al. 2012: 544-545). General floods are typically caused by intense and prolonged rain affecting a large area or by snowmelt.

Flash floods instead refer to highly localized events caused by very heavy but geographically concentrated rainfall temporarily limited to at maximum one day. Storm surges are caused by high winds as part of winter storms or tropical cyclones, while most tsunamis are caused by earthquakes.

Natural disasters can thus involve multiple hazard events. Tropical cyclones for example may also cause flooding and storm surges. Earthquakes may also cause tsunamis and fires. Where multiple hazard events are involved, it is typically impossible to attribute economic losses to individual hazards. As a general rule (see Kron et al. 2012: 538-540 and 544-545 for details), the losses from a tsunami triggered by an earthquake are attributed to the earthquake event. So, for example, the March 2011 natural disaster in Japan, which is not yet in our dataset, would enter as quake damage. For all disasters involving named tropical cyclones, the entire damage is attributed to the tropical cyclone. For all disasters involving both general floods and storms, the loss is generally attributed to the storm events rather than floods, unless there is information that water damage dominates damage caused by wind.

Together, earthquakes, tropical cyclones and general floods account for roughly 70 percent of total disaster damage in the Munich Re dataset, with the rest scattered over the remaining 21 types. Of the estimated sum of disaster damage worldwide over the period 1980 to 2009 of more than 2.8 trillion US\$ (in prices of 2009), 28.8 percent were caused by general floods, 22.8 percent by tropical cyclones and 17.6 percent by earthquakes. The average damage is 212, 363 and 224 million US\$, respectively, but damage is highly skewed with most disasters causing relatively small damage and relatively few disasters causing relatively large damage. Of the almost 3,900 country years with general flood events, 448 caused damage above 100 million US\$ and 98 resulted in damage above 1 billion US\$. For the roughly 1,800

country years with tropical cyclone and the 2,200 country years with quake events, the relevant numbers are, respectively, 394 and 101 for cyclones and 117 and 40 for quakes. That there are more general flood than tropical cyclone and earthquake events is entirely consistent with many more countries and many more regions within countries exposed to flood hazards than exposed to earthquake or tropical cyclone hazards (World Bank 2005: 38).

To appropriately test the predictions derived from our theory, we require measures of hazard strength or magnitude, both in order to control for strength itself but also to construct a proxy for the latent disaster propensity variable (see the discussion below). The Munich Re database contains Richter scale and top wind speed information for the vast majority of quake and tropical cyclone events. It holds no comprehensive and consistent information on precipitation for floods. However, because almost without exception the geographical location of the disaster center is given by degree latitude and longitude, we combine information from the NatCatSERVICE database with precipitation measures taken from Willmott and Matsuura (2011). We acknowledge that the Richter scale is not the only relevant magnitude variable for quakes (see Keefer et al. 2011), nor are top wind speed and precipitation the only relevant magnitude variables for tropical cyclones and floods. However, these measures capture the main destructive forces of the respective hazard events and offer the best available proxy since other relevant magnitude variables (such as focal depth for quakes, minimum air pressure for tropical cyclones or the melting of snow in mountains feeding into upstream rivers for floods) are either not reported for the majority of relevant disaster events or entirely unavailable.

We aggregate the data from the individual disaster event to the country-year level, principally because with a string of events of a particular disaster type the des-

ignation of economic loss to each single event is somewhat arbitrary and does not offer much additional information. For 56.4 percent of our country-years only one event of a specific disaster type had occurred. To arrive at country-year values in years with more than one event of a specific disaster type in a given country, we use the sum of values in a year in a country. Our results are robust toward estimating the same estimation models at the individual disaster event level, which produces results that are statistically indistinguishable from our results at the country year level.

We transform the raw hazard magnitude variables in accordance with what can be known about their likely non-linear impact on economic loss. Given the Richter scale is a base-32 logarithmic scale in terms of the amount of energy set free, which implies that small increases on the scale result in very large increases in unleashed energy (our proxy for hazard strength), we transform the Richter scale magnitude according to the formula  $32^{\text{Richter magnitude}}$  so that the transformed scale measures the energy actually unleashed by the earthquake. Wind speed is typically seen as causing damage as a function of its cubed magnitude (Emanuel 2005; Schmidt et al. 2009). Nordhaus (2010) finds that a 9<sup>th</sup>-power transformation of top wind speed fits US hurricane damage data best, while Bouwer and Botzen (2011) find a best fit for an 8<sup>th</sup>-power transformation. Both sets of authors acknowledge that their estimated best fit power transformations are well above what other studies suggest. We thus take the cube of top wind speeds, i.e. the highest or maximum wind speed reached during the event, as our measure. For precipitation we know of no suggestions on how to account for any potential non-linearity. Monthly data on precipitation on a 0.5 degree latitude and 0.5 degree longitude spatial resolution is provided by Willmott and Matsuura (2011) and we use the absolute precipitation during the flood disaster period from the nearest measurement point to the disaster centre, implicitly assuming that

flood damage is a linear function of precipitation. Ideally, one would like to have data on daily rainfall, but such information is not available. Instead, we attribute monthly rainfall equally across days; longer lasting floods are attributed more rainfall by summing up “daily” rainfall over the period of the disaster.

Compared to the transformed Richter scale as proxy for quake hazard strength, our hazard magnitude variables for tropical cyclones and floods suffer from larger measurement error. What matters for tropical cyclones are wind speeds sustained over some pre-defined short time period rather than top wind speeds as such, which might occur for only a few seconds without being sustained for longer. Unfortunately, the database only records top wind speeds, which will be correlated with maximum sustained wind speeds, but less than perfectly so. For floods, our precipitation measure similarly measures true hazard magnitude only with considerable, probably even larger, measurement error. Floods need not be exclusively caused by local rainfall. Rather, they can be caused by rainfall or the melting of snow in far-away regions where the excess run-off water is carried by rivers downstream causing a flood there. Unfortunately, we have no way of capturing for each of the 1662 general flood events in our sample the relevant area from which the excess water originates. Extending the number of relevant measurement points away from the nearest one to the disaster center would not only increase the likelihood that we capture potentially relevant rainfall in remote places, but also the likelihood that we capture irrelevant rainfall that, for topographical reasons, could never reach the area affected by the disaster.

We use the same sources of information for constructing our central explanatory variable *disaster propensity* – a latent variable. To approximate disaster propensity, we sum over the entire period 1980 to 2008 all the transformed hazard magnitudes separately for each of the three specific disaster events occurring in a country.

This variable has two desirable properties: it is systematically higher the more frequent a country experiences hazards of a certain type and the stronger these hazard events are. For example, the proxy for earthquake propensity takes very high values for Japan and Indonesia given very large quake activity, is high for Iran, medium for New Zealand and low for Germany or Spain with their low quake activity. It might appear problematic to use a value that covers the entire estimation period when this value can only be truly known to individuals and governments at the very end of the period. However, note that these measures proxy for latent and next to time-invariant disaster propensity of countries, such that the value from 1980 to 2008, for which we have data, should be very highly correlated with the values from, say, 1900 to 1979 or from the entire 19<sup>th</sup> century, for which we do not have data.

As control variables we include a country's total gross domestic product (GDP), with data taken from World Bank (2010). All other things equal, countries of larger economic size will have more wealth potentially destroyable and are therefore expected to experience larger losses. Similarly, economic growth leads to a rise in potentially destroyable wealth and disaster losses may even grow faster than wealth (Hallegatte 2011). We have no information on wealth as such, but GDP can function as a proxy. While wealth is a stock and GDP is a flow, wealth and income (GDP) are highly correlated with each other. From the same source comes information on a country's income per capita. There are reasons why richer countries should experience lower damages. Buildings and infrastructure tend to be better constructed in richer countries and thus more likely to withstand the forces of natural hazards than in poorer countries. Also, disaster prevention and damage mitigation measures are costly and both private actors and governments should find it easier to finance such measures in richer than in poorer countries, where economic opportunity cost imposes a

more binding constraint. In economic terminology, disaster prevention and damage mitigation should be normal goods, that is, goods with a positive per capita income elasticity of demand. At the same time, however, richer countries also accumulate more capital seemingly protected by such policies, which means they have higher capital at risk and thus higher economic losses in case of disasters that are not fully prevented (Hallegatte 2011, 2012) The effect of per capita income is therefore ambiguous, given our proxy for wealth will necessarily fail to fully capture the value of capital at risk. Schumacher and Strobl (2011) report non-linear effects of per capita income on damage for earthquakes, but not for tropical cyclones or floods. We find no evidence for non-linear effects for any of our three disaster types and therefore only include the “linear” term.

The sample size depends on whether an economic loss of a specific disaster type is recorded for a country year in the Munich Re database. Country years with no known damage are excluded from the sample. This presupposes that the database captures all relevant natural hazard events of quakes, tropical cyclones and floods – an assumption that can be questioned on various grounds: some hazard events will not have caused damage because of successful prevention measures, smaller disasters from the early years of data collection might have escaped Munich Re’s attention, and disaster events in the developing world are likely to be underreported. Starting with the latter two factors, they provide yet another reason for our quantile analysis: at higher quantiles of the conditional damage distribution under-reporting is not a problem since high damage events will not have escaped Munich Re’s attention or are unreported. As concerns the problem that some hazard events will not have caused damage, as argued in the previous section, in the vast majority of cases hazard events are bound to cause some positive damage despite the best mitigation measures in place.

This will be particularly true for quakes and tropical cyclones. For floods, on the other hand, successful measures, e.g. in the form of dams, might sometimes prevent any recorded damage, such that the estimation results for floods might suffer from selection bias: some country years of damage zero should be in the sample as countries successfully withstood the hazard event, but are not included in the sample since no economic loss occurred. The sample selection makes it less likely that we find empirical support for our hypothesis under the assumption that countries with high propensity are more likely to enact policies that can entirely prevent damage for some hazard events. The relative under-representation of smaller disasters in the early periods of our study does not seem to be severe since in non-reported robustness tests we found neither a linear year variable to be statistically significant nor did we find a trend in year-specific period dummy variables. The relative underrepresentation of damage in the developing world should also not represent a problem for our estimations since, firstly, we control for total economic size in countries and, secondly, any sample selection effect is unlikely to be systematically correlated with disaster strength and disaster propensity as these are not systematically higher or lower in developing countries. The appendix lists the countries included in each of the respective natural disaster event type samples.

We convert the nominal economic loss, GDP and income per capita data into constant US\$ of 1995 using the US GDP deflator. Disaster damage is a highly skewed variable with the vast majority of events causing relatively little damage and only a small minority of events causing very large damage. To reduce skewness, we take the natural log of disaster damage and, as Mendelsohn and Saher (2011) have done before us, estimate log-log models. This allows interpreting the estimated coefficients as



elasticities. Our analysis starts in 1980, the year from which onwards damage estimates were comprehensively collected in the database, and ends in 2008.

#### **4. Results**

Table 1 presents estimation results on the determinants of economic damage from earthquakes. Each column presents estimated elasticities at one of the five quantiles looked at, moving from the .05 quantile on the left to the .95 quantile on the right. Results for the lowest quantile at .05 corroborate our contention that very small damages tend to be random. With the exception of quake magnitude, none of the explanatory variables is statistically significant and the pseudo- $R^2$  value is very low. The explanatory power of the estimation model increases for higher quantiles. As can be seen, disaster damage is higher the stronger the quake magnitude, as one would expect. Its effect increases at higher quantiles, meaning that for higher damages the same increase in unleashed energy results in a larger increase in damage. The estimated elasticity of a country's GDP is smaller than unitary. This is consistent with Mendelsohn and Saher (2011) who similarly find income elasticities below one in their log-log estimation models, using EM-DAT as the source for disaster damage. What this implies is that quake damage increases less than proportionally with a country's GDP as a proxy for the stock of potentially destroyable wealth. Per capita income has no consistent effect on expected quake damage, being statistically significantly negative for only one quantile, the .75 one.

Quake propensity, our central explanatory variable, is estimated to have a negative effect on quake damage throughout, albeit statistically indistinguishable from zero at the bottom quantile. The estimated elasticities increase for higher quantiles and become statistically significant. All other things equal, the effect of quake propensity on expected quake damage is almost four times larger at the .95 quantile than

at the .25 quantile. At the .95 quantile, a ten percent increase in quake propensity lowers expected damage by 2.4 percent, whereas the same increase in quake propensity lowers expected damage by only .8 percent at the .25 quantile. In other words, a very high quake propensity is much more conducive for reducing very large damages than it is for reducing relatively small quake damages. An F-test rejects the hypothesis that the estimated coefficients at the five quantiles are equal at  $p < 0.0004$ , while another F-test rejects the hypothesis that the coefficients at the .25 quantile (i.e., in the middle of the lower half of the distribution) and at the .75 quantile (i.e., in the middle of the upper half of the distribution) are equal at  $p < 0.0037$ . Figure 1a illustrates how the elasticity of quake propensity increases in absolute size as one moves in .05 intervals from the .05 to the .95 quantile.

Table 2 presents estimation results for economic damage from tropical cyclones. As with earthquakes, the explanatory power of the regression model increases, if less strongly, moving from lower to higher quantiles, and damage increases with higher tropical cyclone hazard magnitude. Also similar to earthquakes, damage increases less than unitarily with a country's larger economic size and per capita income has no consistent effect on expected tropical cyclone damages. In fact, at the largest quantile per capita income even has a statistically significant positive effect. This could be because of the larger potentially destroyable wealth in richer countries, which might not be fully captured by a country's total GDP. As concerns tropical cyclone propensity, it has no statistically significant effect at the lower quantiles of the cyclone damage distribution, but it becomes significant at roughly the median of the distribution. An F-test rejects the hypothesis that the estimated coefficients at the five quantiles are equal at  $p < 0.0055$ , while another F-test rejects the hypothesis that the coefficients at the specific .25 and .75 quantiles are equal at  $p < 0.0098$ . Figure 2a

graphically summarizes the changing effect of cyclone propensity on expected damage. After an initial unexpected upward spike at low quantiles, it continuously falls (that is, becomes stronger in absolute terms) from about the .15 quantile onward, but levels off at about the .7 quantile. At high quantiles of the damage distribution cyclone propensity has a stronger effect on expected damage than at low quantiles, but at very high quantiles the effect is not stronger than at high quantiles. At the .75 quantile, a ten percent increase in tropical cyclone propensity lowers expected cyclone damage by about five percent.

Finally, table 3 presents estimation results for flood damage. The estimated elasticities for flood hazard magnitude increase at higher quantiles. As with quakes and tropical cyclones, the estimated elasticity of a country's GDP is less than unitary, but somewhat higher than for these two other disaster types. Apparently, flood damage increases almost proportionally with a country's total economic size. Richer countries experience lower expected damage, an effect that is statistically distinguishable from zero at the lower quantiles up to the median. As concerns flood propensity, similar to the other disaster types there is no significant effect at the lowest quantile looked at. A negative effect starts at the .25 quantile, the effect becomes more negative and statistically significant at the median quantile, decreases in absolute size as well as becoming statistically indistinguishable from zero at the .75 quantile, but increases again in absolute size at the .95 quantile, where it is again statistically distinguishable from zero. An F-test rejects the hypothesis that the estimated coefficients at the five quantiles are equal at  $p < 0.0751$ . A similar F-test cannot reject the hypothesis that the coefficients at the .25 and .75 quantiles are equal, but rejects the hypothesis that the coefficients at the .05 and .95 quantiles are equal at  $p < 0.0165$ . Figure 3a summarizes the effect of flood propensity at continuously varying .05 intervals of quan-

tiles of the flood damage distribution. Note that the 90 percent confidence interval around the estimated elasticities as represented by the shaded area is relatively larger than it was for tropical cyclones propensity, where the confidence interval in turn was larger than was the case for quake propensity. This is to be expected, given, as discussed above, the likely larger measurement error for the cyclone and even larger measurement error for the flood propensity measures and the fact that the flood sample might suffer from sample selection as well. Despite this larger measurement error, which renders it less likely that we find statistically significant evidence for our hypothesis, on the whole it remains true that a higher flood propensity has no effect on avoiding smaller flood damages, but higher propensity predicts lower damage at higher quantiles of the conditional damage distribution. At median flood damage, a ten percent increase in flood propensity lowers predicted damage by an estimated 1.8 percent, while at the .95 quantile, the same flood propensity increase lowers predicted damage by 2.3 percent.

## **5. Robustness tests**

We conducted two sets of important robustness tests. First, our main estimations do not include country fixed effects since our theory makes predictions about the cross-country variation of disaster propensity – a variable that does not change in the short term. However, we tested the robustness of our inferences toward including income group fixed effects (following the classification of countries into low-, lower middle-, upper middle-, high- and high-OECD income groups in World Bank 2010), which accounts for heterogeneity across countries according to their economic development status, as well as a fixed effect for small island nation states (as defined in World Bank 2010), which may be particularly vulnerable (Pelling and Uitto 2001). In addition, we included a measure of insurance penetration (disaster-relevant insurance pre-

mia divided by gross domestic product), directly provided by Munich Re (Barthel and Neumayer 2012), in order to account for the fact that countries with higher insurance penetration are more likely to have disaster damage more comprehensively recorded. Detailed results are provided in the replication data, but figures 1b to 3b graphically show the effect of disaster propensity on each disaster type. Clearly, the results are very similar. For earthquakes, quake propensity has a significantly negative effect over a similar range as in the main estimations, except around the .6 quantile where the relative large confidence interval just so includes the zero threshold. For tropical cyclones, the inferences across the quantiles are also very similar, except for the very last one, in which the effect becomes marginally statistically insignificant. For flood damage, the effect of flood propensity is actually significantly negative for a wider range of quantiles in this robustness test compared to the main estimations. In sum, the corroborating empirical evidence for our theory of natural disaster damage is fully robust to accounting for country group heterogeneity and for differences in insurance penetration rates across countries.

Our second robustness test deals with the fact that all data on natural disaster damage are based on estimates, which carry considerable uncertainty with them. In the opening paragraph of this article, we referred to cost estimates for hurricane Katrina that vary from a low of 82 billion US\$ (Knapp and Brown 2005) to a high of 150 billion US\$ (Burton and Hicks 2005); similarly wide cost estimate intervals will almost inevitably result for the vast majority of other disaster events. We therefore conducted a Monte Carlo study, similar to what Plümper and Neumayer (2009) do for mortality from famines, which aims at exploring the effect of measurement error. Specifically, we re-estimated all models 100 times. In each re-estimation, we injected a random measurement error of up to  $\pm 30$  percent on all observations. By reporting

the full range of coefficients from the Monte Carlo study (minimum to maximum) in table 4 rather than merely the mean, we report the full range of vulnerability of our estimates to measurement error, not just average vulnerability. Measurement error will only be random on average, but it is correlated with the covariates in almost all individual iterations. By looking at the full range of the Monte Carlo estimates, we thus also take some non-random measurement error into account.

We focus on estimates for disaster propensity, our central explanatory variable. As one would expect, the minimum of the Monte Carlo estimates suggest a stronger effect of disaster propensity, while the maximum suggests a weaker effect than the mean of the Monte Carlo estimates, which in turn is close to our main estimation results without induced measurement error. Importantly, however, results are fully robust for all disaster types in the sense that the sign of the maximum of the Monte Carlo estimates is always consistent with the sign of the mean estimate, which in turn is consistent with the results from the main estimates without measurement error injected into the observations. In other words, whenever our main estimations suggest a negative effect of disaster propensity this is not contradicted by either random (mean estimate) or partially non-random measurement error (minimum to maximum) accounted for in the Monte Carlo analysis.

## **6. Conclusion**

Economic damage caused by natural hazards can be mitigated, though typically not entirely prevented. In this article, we explained why individuals and governments often fail to do so. Given individuals face collective action problems, myopic behavior and asymmetric information, successful disaster prevention and damage mitigation in important respects depend on government policies, regulations and interventions. We have argued that the incentives to enact both private and public disaster prevention

and damage mitigation measures strongly depend on the propensity with which a country experiences frequent and strong natural hazards. Where propensity is high, the incentives are high and vice versa where propensity is low. Natural disasters thus cause more damage when a relatively strong outlier hazard hits an area where historically hazard events are infrequent or tend to be of low strength.

We have also argued that the effect of disaster propensity on predicted damage is stronger toward the top end of the conditional damage distribution than toward the bottom end since smaller losses are often unpreventable and tend to be random. We found evidence for this hypothesis in our quantile regressions of damage from earthquakes, tropical cyclones and floods, which together make up nearly three quarters of global economic damage from natural disasters over the period 1980 to 2008.

Our analysis does not answer the question whether the lower prevention and mitigation efforts undertaken in countries with lower disaster propensity is fully rational given the lower frequency or intensity of expected disasters or is sub-optimal. To answer this question one would have to compare the costs of prevention and mitigation efforts to the expected disaster damage costs, which is beyond the scope of this article since we have no information on the costs of prevention and mitigation. For the same reason, it is unclear whether countries with high disaster propensity invest sufficiently in prevention and mitigation measures in response to the high propensity they face or whether even their higher efforts are still below the social optimum. Our theory predicts that prevention and mitigation are likely to be sub-optimal given market and government failures, but we cannot empirically demonstrate this.

One thing we do know is that even where disaster propensity is high, prevention and mitigation can fail and, for the odd strong outlier hazard event, sometimes spectacularly so. For example, dams will be built, but built too low to withstand the

forces of extreme events. Ironically, the existence of a dyke will encourage settlement and investment in high-risk areas so that when the dam breaks fatalities and damage massively increase relative to the counterfactual situation of no dyke. As a result, expected damage for hazard events of “normal” magnitude is much lower, but damage will be larger if an exceptionally strong outlier hazard event hits that nullifies the preventive measures. Both hurricane Katrina and the Tōhoku earthquake demonstrate that extreme economic losses and fatalities are possible despite considerable public prevention and mitigation efforts. In New Orleans, the levees were just “not built for worst case events” (Handwerk 2005) and were inadequately maintained. In Japan, the vast majority of people were not killed and the greatest damage was not caused by the earthquake itself, for which Japan is well prepared, but by the ensuing tsunami, for which it is not. It would have been possible but extremely expensive to protect Japan’s coastline against waves of such height. In future research, we intend to explore further the costs and benefits of disaster prevention and mitigation measures in order to provide better insights into what an optimal policy response to a given disaster propensity would look like.



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Table 1. Economic loss from earthquakes.

Quantile:	.05	.25	.5	.75	.95
ln quake hazard magnitude	0.0818** (0.0380)	0.302*** (0.0341)	0.452*** (0.0441)	0.640*** (0.0416)	0.702*** (0.0801)
ln quake propensity	-0.00755 (0.0197)	-0.0725*** (0.0259)	-0.108*** (0.0343)	-0.207*** (0.0461)	-0.242** (0.103)
ln per capita income of country	0.0387 (0.0542)	-0.0332 (0.0859)	-0.164 (0.118)	-0.404** (0.176)	0.0204 (0.236)
ln Gross Domestic Product of country	0.0722 (0.0540)	0.369*** (0.0528)	0.502*** (0.0831)	0.753*** (0.0875)	0.633*** (0.130)
Constant	-8.000*** (1.545)	-15.80*** (1.132)	-18.69*** (1.497)	-22.07*** (1.577)	-19.60*** (3.720)
Observations	847	847	847	847	847
Countries	117	117	117	117	117
R-squared	0.02	0.12	0.19	0.25	0.24

Note: Dependent variable is the natural log of disaster loss. Bootstrapped standard errors in parentheses, based on 100 iterations.

\*\* significant at .05 level \*\*\* at .01 level.

Table 2. Economic loss from tropical cyclones.

Quantile:	.05	.25	.5	.75	.95
ln tropical cyclone hazard magnitude	1.459*** (0.373)	1.420*** (0.217)	1.607*** (0.159)	1.468*** (0.187)	0.917*** (0.172)
ln tropical cyclone propensity	0.242 (0.206)	0.240 (0.244)	-0.420* (0.233)	-0.524*** (0.166)	-0.370* (0.199)
ln per capita income of country	-0.301 (0.200)	-0.0938 (0.170)	-0.273** (0.111)	0.0728 (0.114)	0.202** (0.102)
ln Gross Domestic Product of country	0.278** (0.129)	0.457*** (0.131)	0.740*** (0.0822)	0.489*** (0.0727)	0.345*** (0.0772)
Constant	-31.72*** (5.950)	-33.87*** (2.889)	-28.67*** (2.749)	-19.61*** (2.312)	-9.898*** (2.637)
Observations	428	428	428	428	428
Countries	62	62	62	62	62
R-squared	0.18	0.22	0.27	0.22	0.27

Note: Dependent variable is the natural log of disaster loss. Bootstrapped standard errors in parentheses, based on 100 iterations.

\* significant at .1 level \*\* at .05 level \*\*\* at .01 level.



Table 3. Economic loss from general floods.

Quantile:	.05	.25	.5	.75	.95
ln flood hazard magnitude	0.272*** (0.0609)	0.540*** (0.0698)	0.733*** (0.0475)	0.751*** (0.0651)	0.714*** (0.0813)
ln flood propensity	0.0672 (0.0802)	-0.122 (0.105)	-0.177* (0.101)	-0.0870 (0.117)	-0.233* (0.0947)
ln per capita income of country	-0.334*** (0.0973)	-0.403*** (0.104)	-0.205** (0.101)	-0.107 (0.0976)	-0.0997 (0.127)
ln Gross Domestic Product of country	0.537*** (0.0605)	0.812*** (0.0812)	0.892*** (0.0759)	0.812*** (0.0761)	0.709*** (0.0988)
Constant	-15.66*** (1.076)	-19.18*** (1.272)	-20.92*** (1.108)	-18.41*** (1.218)	-12.22*** (1.331)
Observations	1,662	1,662	1,662	1,662	1,662
Countries	161	161	161	161	161
R-squared	0.07	0.13	0.20	0.23	0.22

Note: Dependent variable is the natural log of disaster loss. Bootstrapped standard errors in parentheses, based on 100 iterations.

\* significant at .1 level \*\* at .05 level \*\*\* at .01 level.

Table 4. Summary Statistics of Monte Carlo Analysis testing the Robustness of Results toward Measurement Error.

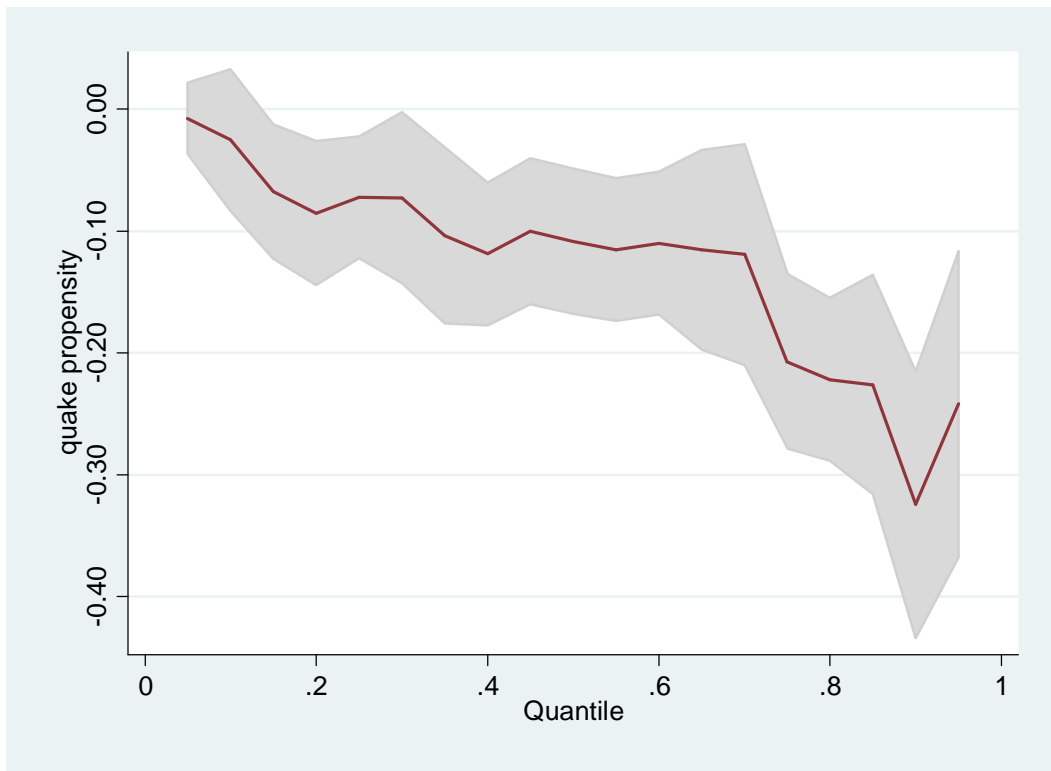
	Mean	Std. Dev.	Min	Max
Quake propensity				
at .05 quantile	-0.0135	0.0096	-0.0364	0.0113
at .25 quantile	-0.2349	0.0285	-0.3442	-0.1827
at .5 quantile	-0.1038	0.0091	-0.1267	-0.0870
at .75 quantile	-0.2090	0.0115	-0.2364	-0.1795
at .95 quantile	-0.2368	0.0278	-0.3109	-0.1806
Tropical cyclone propensity				
at .05 quantile	0.2424	0.0501	0.1252	0.3580
at .25 quantile	0.2455	0.0486	0.1473	0.3528
at .5 quantile	-0.4347	0.0425	-0.5453	-0.3388
at .75 quantile	-0.5513	0.0455	-0.6488	-0.4297
at .95 quantile	-0.3377	0.0751	-0.4842	-0.1602
Flood propensity				
at .05 quantile	0.0633	0.0335	-0.0063	0.1422
at .25 quantile	-0.1065	0.0215	-0.1566	-0.0610
at .5 quantile	-0.1664	0.0218	-0.2241	-0.1234
at .75 quantile	-0.0765	0.0220	-0.1182	-0.0036
at .95 quantile	-0.2420	0.0297	-0.3002	-0.1572

Note: Random measurement error of up to  $\pm 30$  percent injected into all observations.

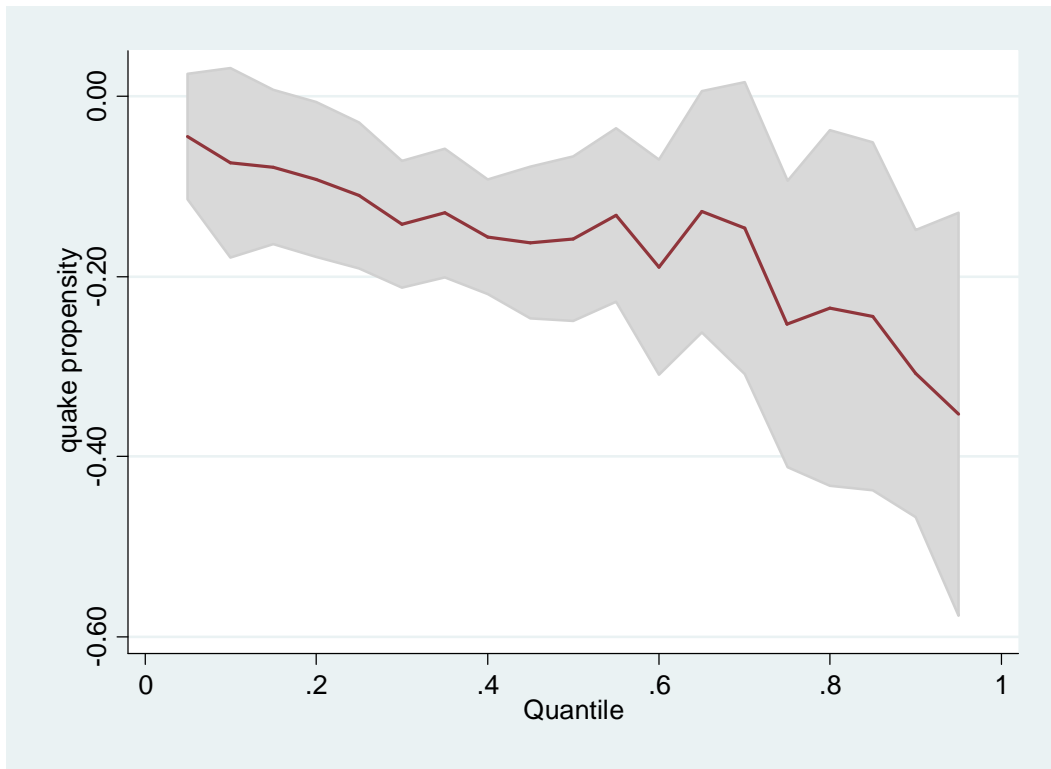
Based on 100 iterations. N = 847 for earthquakes, N = 428 for tropical cyclones and N = 1,662 for general floods.

Figure 1. The effect of quake propensity for varying damage quantiles.

a) Main estimation



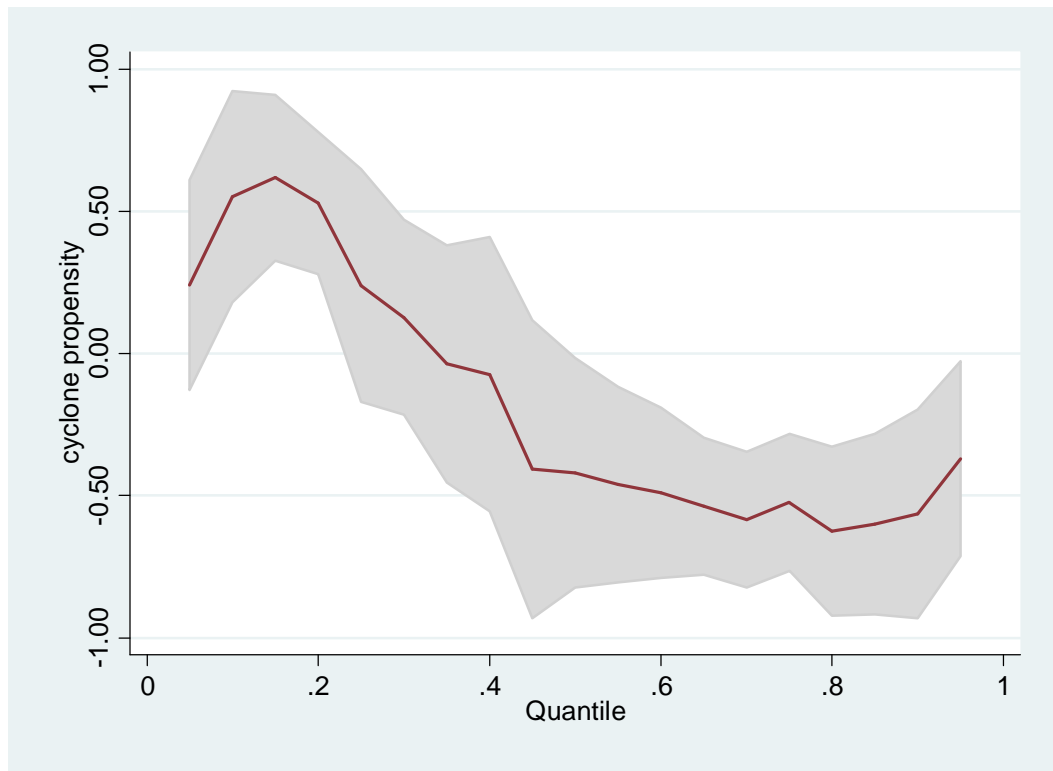
b) Robustness test



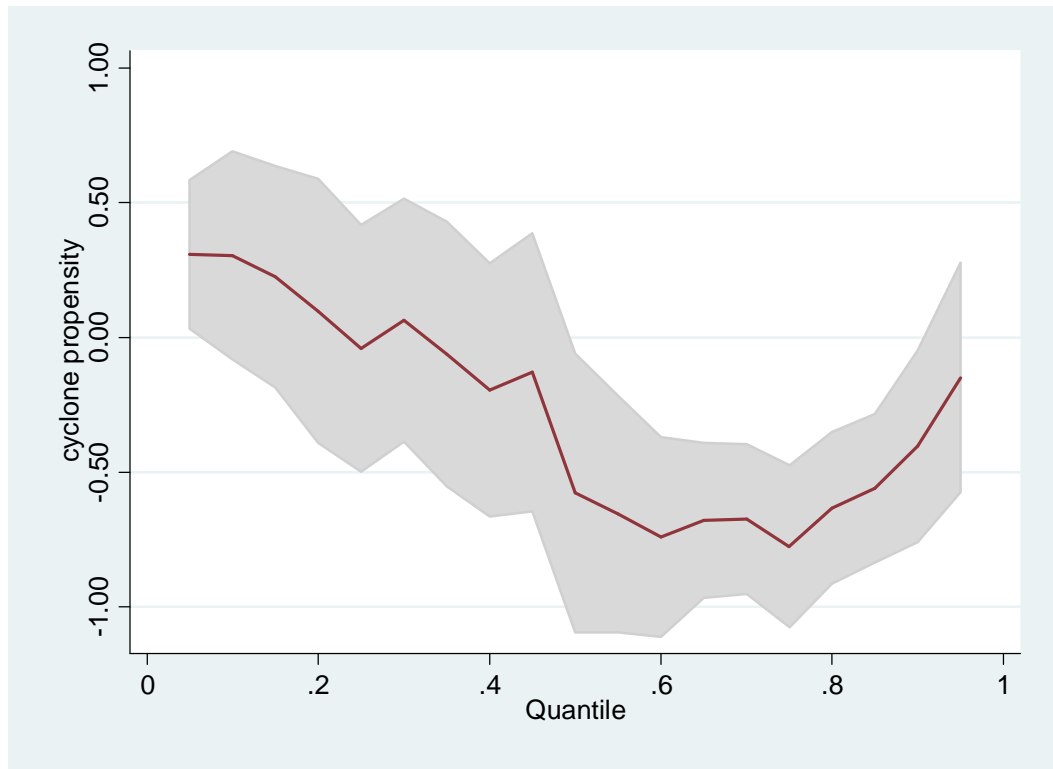
Note: the solid line shows the estimated coefficient, while the grey area represents a 90 percent confidence interval around it.

Figure 2. The effect of tropical cyclone propensity for varying damage quantiles.

a) Main estimation



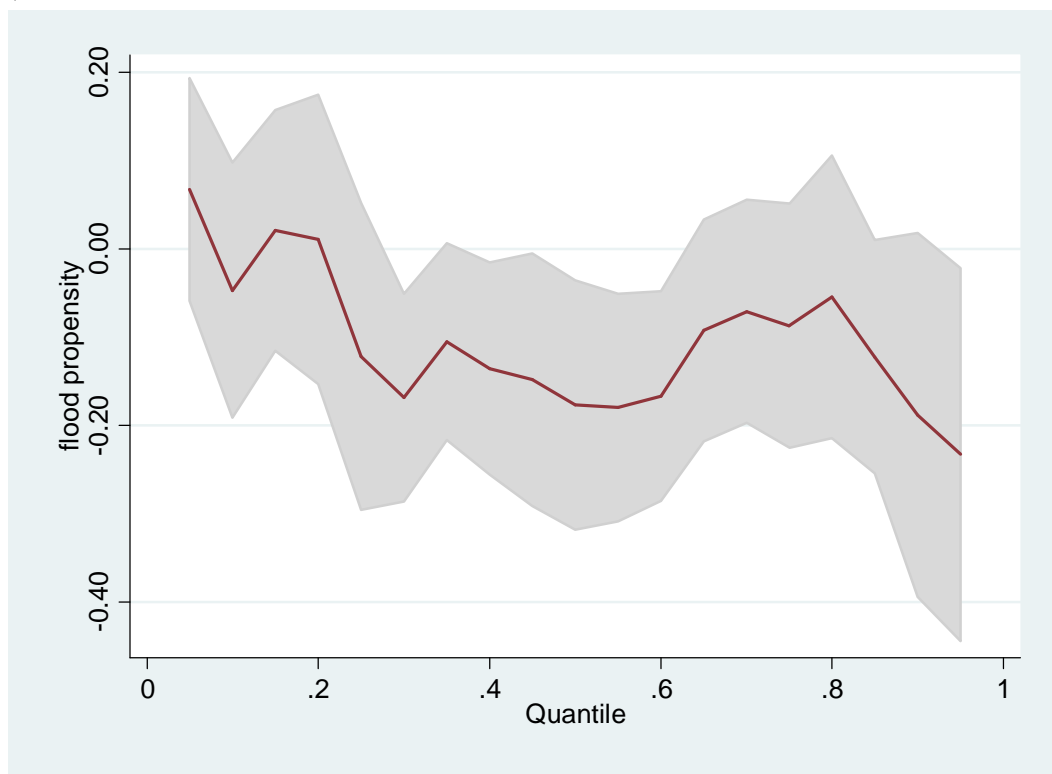
b) Robustness test



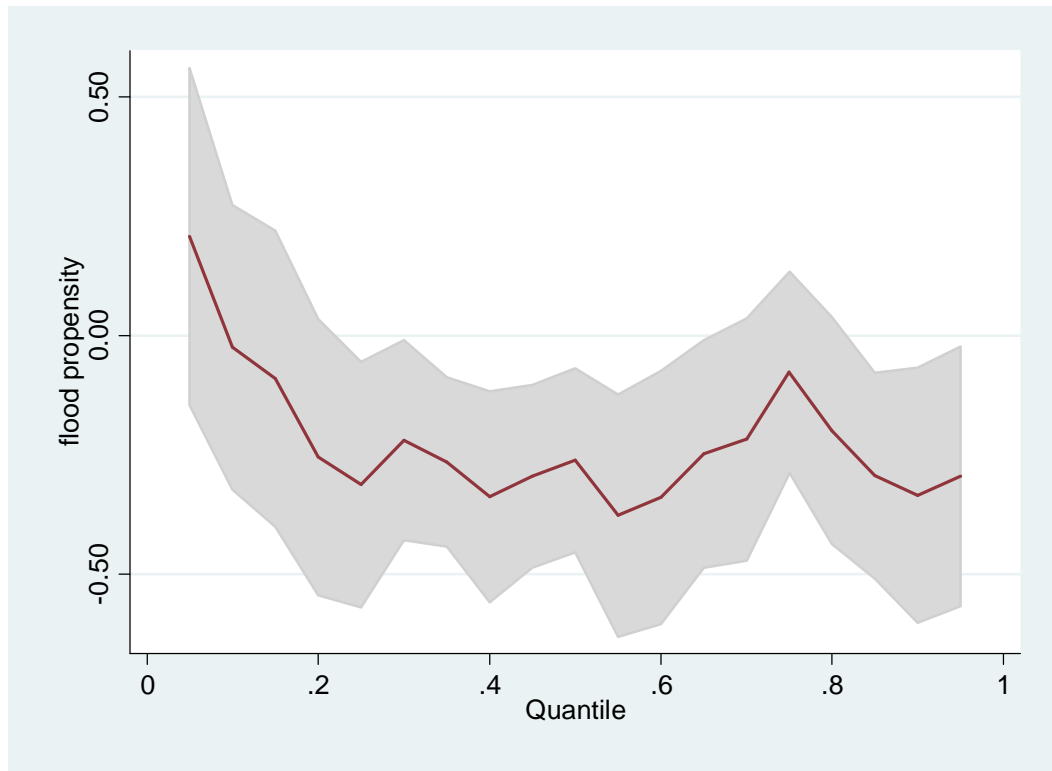
Note: the solid line shows the estimated coefficient, while the grey area represents a 90 percent confidence interval around it.

Figure 3. The effect of flood propensity for varying damage quantiles.

a) Main estimation



b) Robustness test



Note: the solid line shows the estimated coefficient, while the grey area represents a 90 percent confidence interval around it.

## Appendix. Countries included in the samples.

### Earthquakes:

Afghanistan, Albania, Algeria, Argentina, Armenia, Australia, Austria, Azerbaijan, Bangladesh, Barbados, Belgium, Bhutan, Bolivia, Bosnia and Herzegovina, Brazil, Bulgaria, Burundi, Canada, Chile, China, Colombia, Congo (DRC), Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, France, Georgia, Germany, Ghana, Greece, Guatemala, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao PDR, Lebanon, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Mexico, Moldova, Mongolia, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Romania, Russian Federation, Rwanda, Samoa, Saudi Arabia, Seychelles, Slovenia, Solomon Islands, Somalia, South Africa, Spain, Sri Lanka, St. Lucia, St. Vincent and the Grenadines, Sudan, Sweden, Switzerland, Tajikistan, Tanzania, Thailand, Tonga, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, United Kingdom, United States, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

### Floods:

Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo (DRC), Congo (Rep.), Costa Rica, Cote d'Ivoire, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, The, Georgia, Germany, Ghana, Greece, Greenland, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Kuwait, Kyrgyz Republic, Lao PDR, Latvia, Lebanon, Lesotho, Liberia, Liechtenstein, Luxembourg, Macedonia, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Puerto Rico, Romania, Russian Federation, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Singapore, Slovak Republic, Slovenia, Somalia, South Africa, South Korea, Spain, Sri Lanka, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Vanuatu, Venezuela, Vietnam, Yemen, Zambia, Zimbabwe.

### Tropical Cyclones:

Antigua and Barbuda, Australia, Bahamas, Bangladesh, Barbados, Belize, Brazil, Cambodia, Canada, China, Colombia, Costa Rica, Cuba, Dominica, Dominican Re-

public, El Salvador, Fiji, French Polynesia, Grenada, Guatemala, Haiti, Honduras, India, Indonesia, Iran, Jamaica, Japan, Madagascar, Malaysia, Mauritius, Mexico, Micronesia, Morocco, Mozambique, New Caledonia, New Zealand, Nicaragua, Oman, Pakistan, Papua New Guinea, Philippines, Portugal, Puerto Rico, Russian Federation, Samoa, Seychelles, Solomon Islands, South Africa, South Korea, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Swaziland, Thailand, Tonga, Trinidad and Tobago, United States, Vanuatu, Venezuela, Vietnam.