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Analysis

Economic development and losses due to natural disasters: The role of hazard exposure

Ingmar Schumacher [a,b,*], Eric Strobl [b]

[a] Banque centrale du Luxembourg, 2 boulevard Royal, L-2983, Luxembourg
[b] Ecole Polytechnique Paris, Rue de Saclay 91128 Palaiseau Cedex, France

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ABSTRACT

Our contribution is to show that the relationship between wealth and disasters is mainly formed by the exposure to disaster hazard. We first build a simple analytical model that demonstrates how countries that face a low hazard of disasters are likely to see first increasing losses and then decreasing ones with increasing economic development. At the same time, countries that face a high hazard of disasters are likely to experience first decreasing losses and then increasing ones with increasing economic development. We then use a cross-country panel dataset in conjunction with a hazard exposure index to investigate whether the data is consistent with the predictions from the model. In line with our model, we find that the relationship of losses with wealth crucially depends on the level of hazard of natural disasters faced by countries.

1. Introduction

There are certainly few issues more disturbing than the prospect of losing one's hard-earned belongings to the forces of nature. One single instant of a wave, a tremble of the earth, or a passing by of a hurricane is often enough to destroy one's house, one's work, and one's belongings, if not one's life. Periodic news coverage, such as pictures from flooded houses in New Orleans, hurricane-torn houses in Burma, dried fields in Sub-Saharan Africa or the earthquake damages in Chengdu in China, reminds us of this possibility. Unfortunately, from a global perspective such events are a lot more frequent than one might imagine. For example, in 2007 alone there were approximately 450 of these natural disasters worldwide, affecting around 211 million people, and causing economic losses amounting to 74 billion US dollars.[1]

One of the main stylized facts that has arisen from the still relatively new academic literature on natural disasters seems to be that the economic and human losses associated with natural disasters are larger the poorer a country is.[2] This was first shown by Burton et al. (1993) and Tol and Leek (1999) for a sample of 20 nations and later confirmed in more comprehensive studies covering a large panel of countries by Kahn (2005) and Toya and Skidmore (2007). More recently, Rashky (2008), and subsequently Kellenberg and Mobarak (2008), demonstrate that the relationship between damages from natural disasters and income is characterized by an inversely u-shaped relationship, where damages first increase and then decrease with wealth. Yet, surprisingly, beyond arguing, for example, that "as a country develops, it devotes greater resources to safety, including precautionary measures…" (Hideki and Skidmore, p. 20) there are, to our knowledge, few studies investigating the underlying mechanics driving this link, especially those of a theoretical nature.[3, 4]

Arguably a key element in understanding how losses from natural disasters are related to income is the expected hazard of these events. More specifically, Toya and Skidmore (2007) note that there are two relevant components to the disaster–income relationship, namely, (1) increases in income increase the demand for safety, and (2) higher income enables individuals to employ costly precautionary measures in response to this demand. So, if two countries face the same level of hazard one should expect the one with higher income to spend more on precautionary measures and hence to suffer fewer losses if a natural disaster occurs. Similarly, given two countries with equal wealth one would expect the one with a higher hazard to have a higher demand for reducing the exposure to this hazard via precautionary measures.

* Corresponding author. Tel.: +352 4774 4560.
E-mail addresses: ingmar.schumacher@polytechnique.edu (I. Schumacher), eric.strobl@polytechnique.edu (E. Strobl).

[1] Most of these costs are due to storm damages, floods and earthquakes (EM-DAT database).

[2] For example, Anbarci et al. (2005) note that to "say that the level of fatalities resulting from an earthquake is inversely related to a country's per capita level of income is hardly novel" (p. 1907).

[3] Kahn (2005) and Toya and Skidmore (2007) do examine what county characteristics (e.g., education and quality of institutions) are correlated with the relationship between economic development and disaster losses, but only in an ad hoc manner.

[4] While there is a literature that deals with decision-taking under uncertainty and prevention, it has generally not specifically addressed natural disasters. The two main exceptions in this regard are the articles by Lewis and Nickerson (1989), which deals with the amount of self-insurance under uncertainty, as well as Anbarci et al. (2005), which relates inequality and collective action to self-insurance within a natural disaster context.

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Thus, of two equally wealthy countries the one with a lower hazard should suffer greater losses in the case of a natural disaster since it is likely to have invested less in precautionary measures.

Of course, as it is with wealth, the hazard of natural disasters occurring is not evenly distributed across the globe. For instance, tropical cyclones are generally prevalent only in certain coastal areas (ex: US North Atlantic and Gulf of Mexico coastlines, Caribbean Sea, and South Pacific), while major earthquakes are likely to occur in locations where tectonic plates collide (ex: US, Turkey, and Chile). Hence it seems reasonable to assume that the cross-country losses–income relationship is likely to depend on the (expected) hazard of natural disasters that nations face.[5] In other words, if the difference in hazard is large enough then a low hazard country may very well suffer larger losses than a higher hazard country.

In this paper we thus set out to explicitly investigate how this interplay between wealth and hazard affects how natural disaster losses depend on the level of economic development. We, first, develop a theoretical model which is a simplified version of that presented in Schumacher and Strobl (2008), where countries choose their optimal level of prevention expenditure. We pay particular attention to the role of the hazard of a natural disaster. A larger hazard in this model means an increase in the marginal losses in case a disaster hits the country as well as a higher marginal benefit from prevention expenditure. We show that countries facing a low hazard are likely to see increasing losses for low wealth levels, while higher wealth levels lead to decreasing losses if prevention expenditure is sufficiently effective. In contrast to that, high hazard countries will see prevention expenditure even at very low levels of wealth, which leads to decreasing losses for sufficiently effective prevention expenditure. Losses will be increasing with increasing wealth for high hazard countries if further increases in prevention expenditure prove to be less and less efficient. This model helps us in providing an understanding of the driving mechanisms behind the relationship between the economic losses, the natural hazard exposure and economic development.[6]

Using a cross-country panel data set we next investigate whether the empirical evidence is consistent with the predictions of our model. To this end we construct a proxy of country level hazard exposure based on local (within country) risk probability indicators developed by Dilley et al. (2005). We then use this index to explore the role that differences in hazard exposure play in the possibly non-linear income–losses relationship, as suggested by our theoretical model. Our econometric analysis demonstrates that the shape of the relationship between wealth and losses crucially depends on the hazard of natural disasters that countries face. More precisely, we generally find an inverse u-shaped link between losses and wealth for low and medium hazard countries, but a u-shaped relationship for high hazard countries. These results are robust to the implementation of alternative methodological approaches previously used in the literature.

The remainder of the paper is organized as follows. In the following section we outline our theoretical framework and its implications. In Section **3** we describe our data set. Our econometric specification and results are contained in Section **4**. The final section concludes.

2. Theoretical Model

Our intention here is to capture the essential relationship between economic development, prevention expenditure and the costs of natural disasters. The model presented here is a simplified version of that in Schumacher and Strobl (2008), which extends Lewis and Nickerson (1989), where we introduce risk over the state of nature and uncertainty over the extend of the damage. The predictions of the two models are very similar. We assume that a country (or a region) maximizes utility $u(I)$, which is a function of net wealth, $I=w-cx-L(w,x,y)>0$, where wealth is given by $w>0$, prevention expenditure $x\geq 0$ comes at marginal cost $c>0$, and losses are given by $L(w,x,y)$. Here, $y>0$ represents the strength of a disaster, where a larger y implies a stronger disaster. The functional forms assumed are $u_I>0$, $u_{II}<0$, $L_w>0, L_x<0, L_y>0, L_{xx}>0, L_{xy}<0, L_{xw}$. All variables are in totals.

Intuitively, our assumptions imply that the amount of wealth destroyed increases in the amount of wealth available, but is reduced by higher prevention expenditure, while stronger disasters increase losses. Furthermore, increasing prevention expenditure is expected to be less and less effective, and prevention expenditure is assumed to be more effective for larger disasters. Finally, we also assume $L_{xw}<0$, implying that the marginal loss for a given wealth level decreases in prevention expenditure. This last assumption is not innocuous and drives our subsequent results. It implies that the more a country spends on prevention expenditure, the lower will be the losses per unit of wealth increase. This seems a reasonable assumption also for the kind of larger scale disasters that we focus on empirically later.[7] Intuitively, imagine a hurricane that landfalls in a city. The more the city spends on adapting the housing to a hurricane strike the less will each house be affected by the hurricane. Or, in other words, for a low level of prevention expenditure, we expect the marginal loss per unit of wealth increase to be larger than for high levels of prevention expenditure.

The approach presented here can be read in two ways. Firstly, it can be viewed as a simplified model of Schumacher and Strobl (2008), capturing the essential underlying relationships between disaster hazard, wealth and prevention expenditure.

Secondly, one would ideally want to model the hazard of a natural disaster as a risky event, with a given distribution $p(g)$, and thus the expected event would be $y=E(g)=\int_0^\infty gp(g)dg$. Thus, $g=0$ would be the case of no disaster, while $g=\infty$ would indicate the worst possible scenario. On average, the expected event would then be $h=E(g)$. Thus, our function $L(w,x,y)$ indicates the expected, or average loss. A country with a larger hazard would then be one where the function p(g) attaches higher probabilities to states of the world with larger g's, i.e. with worse events. In a slightly different interpretation, we could view this model as one where a policy maker takes into account that with a certain probability the protection might fail. For example, we could write $L(w,x,y)=(1-y)\cdot 0+y\cdot\hat{L}(w,x)$. Thus, in this case $y\in(0,1)$ and it would be interpreted as the probability that the protection fails and a loss $\hat{L}(w,x)$ is incurred. Prevention expenditure would then become relevant when the protection fails. Interpreted in this way, then the model is more suitable for disasters for which one cannot influence the probability that protection fails but only the final losses, for example hurricanes.[8]

As yet another interpretation[9] we could write $\mathrm{L(w,x,y)} = \mathrm{h(x,y)}\ 0 + (1\text{-}\mathrm{h(x,y)})\ \tilde{L}\ (\mathrm{w})$, with $h_x>0$ and $h_y<0$. In this case, the probability of a disaster creating a loss, i.e. the probability of a failure in the defenses, is decreasing with the prevention expenditure. The actual damages themselves, however, do not depend on the prevention expenditure but only on the exposed wealth. This interpretation would then be a useful one for studying disasters like flooding, since dams may reduce the probability that an event induces a loss. However, once a dam breaks the actual loss is only depending on the exposed wealth.

[5] Neither Toya and Skidmore (2007) nor Kahn (2005) explicitly takes account of expected risk in this regard.

[6] Hallegatte (2011) has recently developed a model showing that disaster losses can grow faster than wealth. He shows that it may be beneficial to invest in riskier regions with increasing economic development.

[7] Specifically, by this we mean those disasters that are sufficiently large as to have made their way into the EM-DAT database, which we use for our empirical study.

[8] Hence, it would be less suited to study flooding, since in this case one can mainly influence the probability that the event materializes in a loss by building a sufficiently high dam.

[9] We are grateful to the editor for suggesting this interpretation.

We now turn to derive the main intuitions from this simple model, which we collect in the following propositions. The proofs are presented in a didactic way.

Proposition 1. *Ceteris paribus,* $\exists\hat{y}$*, such that* $\forall y>\hat{y}, x>0$*, while* $\forall y\leq\hat{y}, x=0$*. Furthermore, ceteris paribus,* $\exists\hat{w}$*, such that* $\forall w>\hat{w}, x>0$*, while* $\forall w<\hat{w}$*,* $x=0$*.*

If we maximize the utility function with respect to the control $x\in[0,w/c]$ then we obtain

$$-L_x\leq c,$$

with equality if $x>0$. If the marginal benefits from prevention expenditure L_x exceed the marginal cost c, then it would be optimal to increase prevention expenditure until both are equal. On the other hand, if the marginal benefits from prevention expenditure are lower than the marginal costs, then no prevention expenditure should be undertaken. In this case we will observe a corner solution with $x=0$. It is easy to show that, for a given >0, $\exists\hat{y}$, such that $\forall y>(<)\hat{y}, x>(=)0$. Furthermore, for a given $y>0$, $\exists\hat{w}$, such that $\forall w>(<)\hat{w}, x>(=)0$. Both results derive directly from the first-order condition and the assumptions on the loss function. Intuitively, if either wealth is high enough or the disaster is expected to be sufficiently strong, then prevention expenditure will be positive. Thus, low-hazard countries are unlikely to undertake prevention expenditure, while high-hazard countries should invest in prevention, and increasing wealth is more likely to lead to prevention.

Proposition 2. $\exists(\hat{y},\hat{w})$ *such that* $\forall y<\hat{y}$ *and* $\forall w<\hat{w}$*,* $\frac{dL}{dw}>0$*. Furthermore,* $\frac{dL}{dw}<(>)0$ *if* $\frac{L_w}{L_{wx}}>(<)\frac{L_x}{L_{xx}}$*.*

The change in prevention expenditure when wealth changes is given by

$$\frac{dx}{dw}=-\frac{L_{xw}}{L_{xx}}>0.$$

Therefore, not only do we find that increasing wealth may drive a country from a corner solution in prevention expenditure to an interior solution, in addition we conclude that prevention expenditure increases with higher wealth.

We now pay particularly close attention to the role of hazard along a country's path of economic development. As losses are given by $L(x,w,y)$, then economic losses respond to changes in wealth as follows:

$$\frac{dL}{dw}=L_w+L_x\frac{dx}{dw}.$$

As derived in Proposition 2, for a given level of wealth there exists a $\hat{y}$ such that for all $y<\hat{y}$, we obtain a corner solution with $x=0$. Thus, we can derive that, for a sufficiently low w and if $y<\hat{y}$, then

$$\frac{dL}{dw}=L_w>0,$$

which implies that losses are increasing in wealth if the hazard is low. This suggests that it would not be worthwhile to invest in prevention expenditure if the additional costs of prevention expenditure do not sufficiently compensate for the marginal losses in wealth. If a country's wealth keeps increasing, then $\exists\hat{w}>0$, such that $\forall w>\hat{w}$ we have $x>0$, which implies that undertaking prevention expenditure becomes worthwhile. Thus, at an interior solution for $0<x<w/c$ we obtain $\frac{dL}{dw}=L_w+c\frac{L_{xw}}{L_{xx}}$. Furthermore, if $\frac{L_w}{L_{wx}}>\frac{L_x}{L_{xx}}$, then $\frac{dL}{dw}<0$. In this case, increasing prevention expenditure reduces total losses. The condition $L_w<L_x\frac{L_{xx}}{L_{xx}}$ has an intuitive interpretation. $L_w>0$ suggests that, ceteris paribus, economic development increases losses from disasters. If a planner undertakes prevention expenditure, then this, firstly, changes the ‘growth rate’ in L_x (which is defined as $\frac{dL_x}{dx}/L_x$), and secondly it reduces the marginal losses from increases in wealth.

As shown in Proposition 2, for sufficiently high hazard countries, we will see an interior solution in prevention expenditure even for very low levels of wealth. In this case, $\frac{dL}{dw}<0$ if $\frac{L_w}{L_{wx}}>\frac{L_x}{L_{xx}}$. Once a significant amount of prevention expenditure has been undertaken, then the marginal benefit from undertaking additional prevention expenditure will be low. This would imply that $\frac{dL}{dw}>0$ if $\frac{L_w}{L_{wx}}<\frac{L_x}{L_{xx}}$.

In the case where prevention expenditure affects the probability of a disaster but not the actual losses, then the economic loss-wealth relationship would simplify to $\frac{dL}{dw}=\widetilde{L}_w\left(1+\frac{h_x^2}{h_{xx}}\right)$. Thus, whether losses increase or decrease with wealth then depends only on how the effectiveness of the defenses changes with increasing prevention expenditure.

To sum up, we have shown that low hazard countries are unlikely to undertake prevention expenditure for low levels of wealth while with increasing development these countries will find prevention expenditure more profitable. If, furthermore, an increase in wealth leads to prevention expenditure that compensates for the additional loss incurred in case a disaster occurs, then total losses will decrease along the path of economic development.

In contrast to low hazard countries, we have shown that high hazard countries will undertake prevention expenditure even at very low levels of wealth, and will see decreasing losses with increasing wealth if the marginal benefits from prevention expenditure outweigh the costs. This is likely to lead to decreasing losses along the path of economic development. As one can easily argue, the potential for prevention expenditure is not unlimited and marginal benefits from further prevention expenditure will be declining. This effect should be more significant for high hazard countries than for low hazard ones. In that case, we are likely to see increasing losses with higher levels of wealth.

Thus, we have shown that high hazard countries are likely to have a u-shaped relationship between wealth and economic losses, while low hazard countries are likely to have an inversely u-shaped one.

The model, due to its generality and minimalistic assumptions on the functional forms, certainly leaves several aspects open. Nevertheless, it provides an intuitive explanation for the way natural hazards affect prevention expenditure and thus losses along a country's path of economic development. To obtain a concrete idea about these relationships, we now turn to our empirical study that disentangles the aspects empirically.

3. Data

3.1. Hazard Exposure Data

An important aspect of our study with regard to investigating whether the data are consistent with predictions of our theoretical model is a proxy for the expected hazard of a natural disaster. From an empirical perspective ideally one would thus like to have some sort of indicator of the probability density function for natural disaster which describes the probability of occurrence along the complete range of intensities. In order to derive such a proxy we avail of the natural disaster global hot-spots data constructed by a joint effort from the World Bank Hazard Management Unit and the Center for Hazards and Risks Research Unit at Columbia University (see Dilley et al. (2005)). More specifically, this research team developed an innovative summary proxy of hazard exposures faced locally (within countries) across the globe. It takes account of both the likelihood of a natural disaster event as well as the local exposure to it (in terms of population) for five different natural disasters: cyclones, earthquakes, landslides, floods, and droughts. Details of their methodology are given in the Data Appendix.

Since the multi-hazard index by Dilley et al. (2005) is calculated for local sub-national level grid cells we derive a national measure of natural disaster (per capita) hazard by summing grid cells' multi-hazard values within countries and normalizing this sum by a

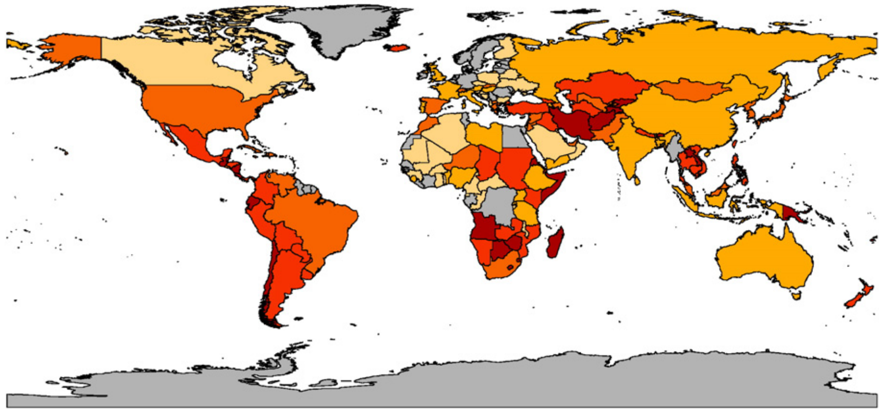

Fig. 1. Distribution of HZ. Note: (1) Gray colored areas indicate zero value. (2) Darker shading of non-gray colored countries indicates greater value of HZ.

country's population size (in '000 s) in 2000 as given by the GPW data.[10] We depict our country level proxy of natural disaster hazard in Fig. 1. The graph demonstrates the unequal distribution of hazard exposure across the globe. Although not easily detectable from the graph, the highest hazard countries are, unsurprisingly, mostly small islands – as, for example, Vanuatu, Turks and Caicos Islands, and Belize – although also some larger countries also feature in the very hazardous groups (ex: Somalia, Afghanistan, and Chile).

3.2. Economic Loss Data

The loss due to natural disasters data that we use are compiled from the now well-known EM-DAT database maintained by the Centre for Research on the Epidemiology of Disasters (CRED) which compiles information on natural disasters across countries over time, where natural disasters are defined as natural events that overwhelm local capacity, necessitating a request for assistance from national or international levels. The information underlying the data is derived from a variety of sources, including international and research institutions, insurance companies, and press agencies. In order for an event to be considered a natural 'disaster' it must report having caused deaths of at least ten people, having affected at least 100 people, resulted in a call for international assistance, and/or resulted in a declaration of a state of emergency. Given the definition of our multi-hazard measure we limit our analysis to economic losses due to windstorms, droughts, earthquakes, floods, landslides, and volcanoes as defined by the EM-DAT database. The average yearly per capita losses are depicted in Fig. 2.[11] Accordingly, even within continents there are notable differences in the economic losses due to natural disasters. If one examines the group of countries with the greatest losses, one discovers that this includes both developed (ex: US and Japan) as well as developing nations (ex: Philippines and Mexico).

3.3. Other Data

Our time-varying country level measure of GDP per capita is taken from the World Penn Data Tables. Additionally, we use its estimate of (time varying) population size. Finally, a measure of geographical size of each country is taken from the Global Rural–Urban Mapping Project (GRUMP).

3.4. Sample

Although in principle the data required for our estimation could start from 1960, one should note that we restrict our sample to cover the period 1980–2004.[12] This is done for two reasons. Firstly, while for some of the underlying disaster types the hazard indicators are derived from time invariant data or data over long time periods, for others this would have been constructed from data available from roughly the 1980s onwards. If the local probabilities of occurrence along the complete range of intensities of these disasters vary over time then our proxy may not be representative of the actual distributions for the period prior to 1980. Secondly, there may be some concern that particularly for earlier years the quality of the EM-DAT database may have been poor (see Strömberg (2007)). Restricting our sample period to observations from 1980 onwards and using only observations where the non-missing values on all variables used in our analysis resulted in a total sample size of 4144 covering 181 countries. A set of summary statistics for all variables is provided in Table 1.

4. Econometric Analysis

Our primary empirical purpose is to investigate whether the data is consistent with the predictions from our theoretical framework. In this regard we start off with the base specification relating economic losses to the level of economic development:

$$\log\left(\frac{\mathrm{LOSSES}_{i,t}}{\mathrm{POP}_{i,t-1}}+1\right) = \alpha + \beta_1 \log\left(\frac{\mathrm{GDP}_{i,t-1}}{\mathrm{POP}_{i,t-1}}\right) + \beta_2 \log\left(\frac{\mathrm{GDP}_{i,t-1}}{\mathrm{POP}_{i,t-1}}\right)^2 + \lambda_j \sum_{j=1}^{m} X_{i,t-1} + \varepsilon_{i,t} \quad (13)$$

where i is a country indicator and t a time subscript. $\frac{\mathrm{LOSSES}_{i,t}}{\mathrm{POP}_{i,t-1}}$ are a (per capita) measure of economic losses due to natural disasters as taken from the EM-DAT database, $\log\left(\frac{\mathrm{GDP}_{i,t-1}}{\mathrm{POP}_{i,t-1}}\right)$ is a measure of economic development (wealth) as taken from the World Penn Tables and included both in levels and in quadratic form to capture its arguably non-linear relationship to losses, $\sum_{j=1}^{m} X_{i,t-1}$ is a set of other possibly time and/or cross-country varying control variables, and $\varepsilon_{i,t}$ is an error term. In terms of other control variables we include the logged value of national population density and the logged value of the total geographical area of a country, as well as a set of year dummies.

[10] One may want to note that we use the population size in 2000 since the population density data weighting scheme of our measure is also derived from 2000 data.

[11] While our benchmark measure of losses due to natural disasters are the monetary losses just described, one should note that we also experiment with using deaths as a proxy; see the end of Section 4.

[12] One should note, however, that including the earlier data in our analysis did not change the results qualitatively and little quantitatively.

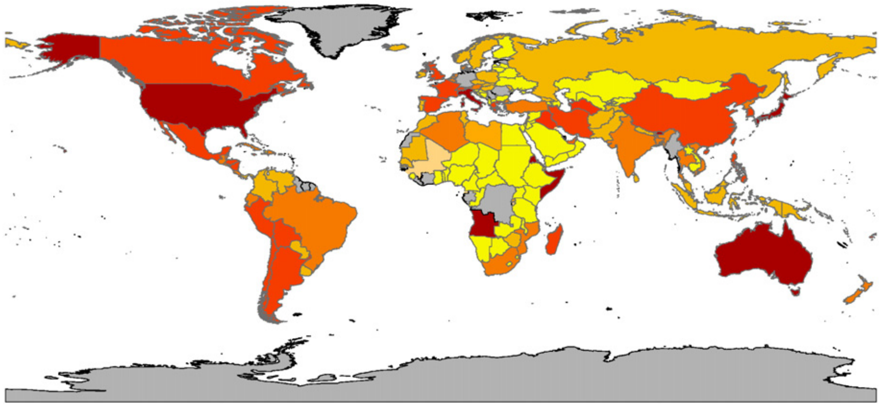

Fig. 2. Distribution of LOSS. Note: (1) Gray colored areas indicate zero value. (2) Darker shading of non-gray colored countries indicates greater value of per capita losses.

One should note that the dependent variable in Eq. (13) consists of a large number of zeros since many countries for many years experience no economic losses, which may be due to no disasters occurring in that year or potential disasters not translating into economic losses. This renders standard Ordinary Least Squares inappropriate as an estimation methodology and we hence resort to using a tobit estimator which explicitly deals with such lower truncation in the data. To take account of potential heteroskedasticity and correlation of observations across time within countries, we calculate robust standard errors allowing for within-country clustering of the error term.

Finally, though the theoretical model is in totals, in the empirical part we use per capita terms. This we do in order to incorporate changes that may arise due to population growth.

4.1. Main Results

The estimates of our base specification in Eq. (13) are given in Table 2. As can be seen, the significant coefficients on log($AREA_i$) and log($POP_{i,t-1}/AREA_i$) indicate that per capita economic losses due to disasters increase with geographical size and greater population density of a country. More importantly, both GDP per capita and its squared value are found to be statistically significant. The signs of their coefficients suggest an inverted u-shaped relationship between economic losses and economic development, as found by Rashky (2008) and Kellenberg and Mobarak (2008). Calculations using the estimated coefficients indicate that the turning point occurs at a point slightly above the mean level of GDP per capita (at a value of 9.48), which roughly corresponds to the wealth of a country like Chile — after which the level of development and economic losses have a negative relationship.

We next include our natural disaster multi-hazard measure in Eq. (13), denoted as *HZ*, in the second column of Table 2. Accordingly, its inclusion first of all noticeably changes the size of the coefficients on our indicator of development and its value squared. This demonstrates that not controlling for differences in hazard exposure will bias the estimated economic loss–development relationship. Under these new coefficients the turning point is predicted to be later (at a logged GDP per capita value of 10), i.e., around the level of development of New Zealand. Our country-level proxy of hazard exposure is found to have a significant positive effect on economic losses suffered.

In the third column of Table 2 we interact our hazard proxy with GDP per capita in levels and its squared term to see whether the wealth–loss relationship depends on disaster hazard. As can be seen, both the slope of the wealth-development link as well as its rate of change significantly depends on the probability of a natural hazard of a country. More specifically, the signs on the interaction terms indicate that the more exposed a country is to natural hazards the flatter its inverted u-shaped relationship will be. In other words, for countries where natural disasters are more likely, greater wealth will have a reducing effect on economic losses suffered at a later stage of development and at a lower rate. In Fig. 3 we depict the implied wealth–loss relationship for when the hazard is 0 and at the 20th, 40th, 60th, and 80th percentile of its non-zero distribution in our data. As can be seen, the zero, 20th, 40th, and 60th percentile curves are all inverted u-curves, while at the 80th percentile the shape is reversed. Simple calculations show that this 'reversal' occurs around the 70th percentile.

4.2. Robustness Analysis

We also conduct a number of robustness checks. Firstly, the distribution of our multi-hazard index is extremely skewed where the value for some countries is a multifold of the average. Feasibly, these extreme outliers could be driving our results. To investigate this we re-ran the specification in the third column, but excluded all countries for which the hazard rate was above the 90th percentile of its distribution, i.e., above values of 45. As can be seen, not only are the results qualitatively, but also quantitatively very similar to before.

One may also want to note that although the economic loss data is the most comprehensive collection of information on costs of natural disasters across countries over time available, it has some shortcomings (see Toya and Skidmore (2007)). First of all, the data on damages suffered due to the natural disasters generally includes only direct, and not

Table 1
Summary statistics.

Variable	Mean	St. dev.
$LOSS_{all}$	0.442637	1.198036
Log($GDP/POP_{i,t-1}$)	8.303593	1.13478
HZ	22.71573	33.6286
Log($POP/AREA_{i,t-1}$)	−3.02509	1.587856
Log($AREA_{1}$)	11.44056	2.584813
$LOSS_{EQ}$	0.057564	0.454302
$LOSS_{LS}$	0.007359	0.150434
$LOSS_{CY}$	0.213984	0.911184
$LOSS_{FL}$	0.157363	0.626108
$LOSS_{DR}$	0.042535	0.383609
$LOSS_{VO}$	0.005302	0.130794
$DEATH_{EQ}$	0.005335	0.0596863
$DEATH_{EQ}$	0.001828	0.040488
$DEATH_{LS}$	0.00035	0.009327
$DEATH_{CY}$	0.001874	0.029065
$DEATH_{FL}$	0.001029	0.013799
$DEATH_{DR}$	0.001869	0.056977
$DEATH_{VO}$	0.000138	0.007362
ENERGY	0.340081	1.512644

Notes: (1) Summary statics for regression sample only; (2) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.
(3) ENERGY is multiplied by 10^{14}.

Table 2
Multi-hazard regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*DEATH*	*LOSS*
$\text{Log}(\text{GDP}/\text{POP}_{i,t-1})$	7.043***	5.312***	7.381***	7.071***	0.141**	8.467***
	(2.110)	(1.952)	(2.382)	(2.633)	(0.055)	(3.021)
$[\text{Log}(\text{GDP}/\text{POP}_{i,t-1})]^2$	−0.367***	−0.258**	−0.396***	−0.374**	−0.009***	−0.432**
	(0.126)	(0.118)	(0.142)	(0.158)	(0.003)	(0.180)
HZ_i		0.023***	0.745**	0.848**	0.010*	1.139***
		(0.006)	(0.334)	(0.421)	(0.006)	(0.437)
$\text{Log}(\text{GDP}/\text{POP}_{i,t-1})*\text{HZ}_i$			−0.191**	−0.208**	−0.003*	−0.281***
			(0.078)	(0.102)	(0.001)	(0.102)
$[\text{Log}(\text{GDP}/\text{POP}_{i,t-1})]^2*\text{HZ}_i$			0.013***	0.013**	0.000**	0.018***
			(0.005)	(0.006)	(0.000)	(0.006)
$\text{Log}(\text{POP}/\text{AREA}_{i,t-1})$	0.841***	1.028***	1.051***	1.038***	0.030***	1.139***
	(0.119)	(0.126)	(0.126)	(0.129)	(0.007)	(0.165)
$\text{Log}(\text{AREA}_I)$	0.686***	0.768***	0.768***	0.727***	0.027***	0.786***
	(0.061)	(0.059)	(0.059)	(0.063)	(0.006)	(0.081)
Constant	−42.211***	−36.463***	−43.883***	−42.604***	−0.910***	−51.820***
	(8.716)	(7.984)	(9.822)	(10.799)	(0.240)	(12.353)
Sample:	ALL	ALL	ALL	$\text{HZ}_i<45$	ALL	CY,DR,EQ,LS
Observations	4144	4144	4144	3685	4144	4144
Left Cens.	3136	3136	3136	2783	2766	3466
Pseudo R^2	0.0720	0.0839	0.0901	0.103	5.925	0.0787

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10% significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.

indirect, costs. Additionally, there is the possibility that reported damages may be exaggerated in order to secure greater international assistance. Finally, there may be some suspicion that data is of poorer quality for developing countries, since these tend to have less insurance coverage, poorer bookkeeping, and more informal markets. As an alternative measure we thus also experiment with the (logged) number of deaths per capita, also given in the EM-DAT database, under the assumption that human losses are likely to be correlated with actual monetary losses.[13] The results of using this alternative dependent variable in our specification with all interaction terms are given in the fifth column of Table 2. Reassuringly, one finds qualitatively similar coefficients as for the economic loss data.

Thus far we have treated all six disasters as one homogenous group by using a multi-hazard index in our analysis. Feasibly, however, disasters may have very different effects on the wealth–loss relationship. Moreover, as discussed above, the underlying hazard measures come from very different data sources, where some are based on actual events (windstorms, floods, volcanoes, droughts), some on time-invariant probabilistic measures (landslides), and others on both (earthquakes). Additionally, these data sources differ in their quality.[14] To investigate whether our general results hold across disasters types we calculated analogous country-level measures of hazards for each disaster type (i.e., by not summing across hazards). Re-defining the dependent variable to only consider losses of the disaster type in question, we first re-ran our specification for each disaster type separately in Table 3. Accordingly, for all disaster types the hazard measure has a positive and significant effect on losses, hence providing some support that these are appropriate proxies of the probability of a disaster occurring along the range of severities. One may want to note in this regard that in this base specification, however, for both windstorms and landslides there appears to be no relationship between losses and economic development.[15]

We next generated and included the necessary interaction terms to replicate the specification from the third column in Table 2 for each disaster type. The results of this are given in Table 4. Firstly, one may want to note that there is now a significant wealth–loss relationship for all disaster types, although not always non-linear. Moreover, in terms of our interaction terms for three of the six disaster types, namely, windstorms, earthquakes, and landslides, we get similar qualitative results to our multi-hazard regression, except that for windstorms the lack of significance on the squared logged GDP per capita terms indicates that any non-linear effect of wealth on losses only acts through reducing the dampening effect of being subjected to a greater probability of windstorms. In contrast, being more hazardous in terms of droughts, floods, or volcanoes does not appear to influence how greater development affects economic losses.

We also experimented with using our alternative proxy for losses, i.e., the logged deaths per capita, for the different disaster types, as shown in Table 5. Here one discovers that the results derived from the multi-hazard analysis holds across four different disaster types, namely windstorms, earthquakes, droughts, and landslides. In

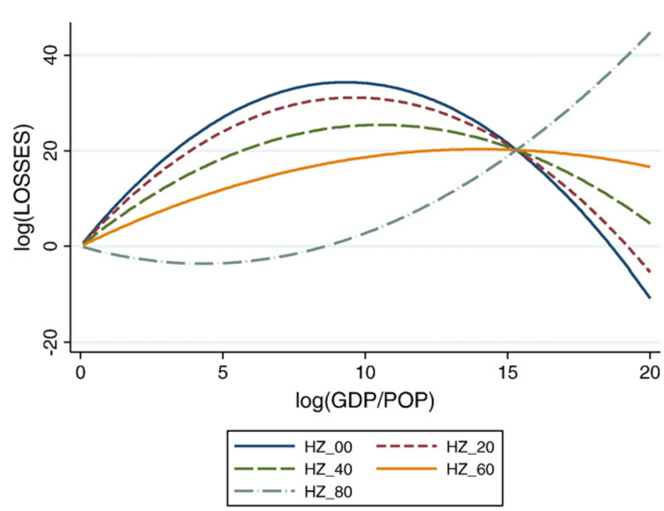

Fig. 3. The losses–wealth relationship by natural disaster hazard level.

[13] The correlation between the reported number of deaths and the reported number of losses was found to be positive and statistically significant.

[14] For example, the flood data is known to be poor for parts of the 1990s. There is also some suspicion that the cyclone data may differ in quality across regions. Finally, although there is something to be said for using a uniform definition of drought, such as the weighted anomaly of standard precipitation, there is some skepticism in the literature whether a single measure can be appropriate for all regions of the globe; see, for instance, Bhalme and Mooley (1979).

[15] This holds even when we exclude the squared term of logged GDP per capita.

Table 3
Single hazard regressions — No interaction effect.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*
$\text{Log}(\text{GDP/POP}_{i,t-1})$	3.426	8.401**	4.654	3.138**	11.345**	8.568**	8.900***
	(3.116)	(4.130)	(3.441)	(1.235)	(5.454)	(3.841)	(0.017)
$[\text{Log}(\text{GDP/POP}_{i,t-1})]^2$	−0.125	−0.457*	−0.230	−0.159**	−0.638**	−0.456**	−0.458***
	(0.187)	(0.241)	(0.208)	(0.074)	(0.317)	(0.223)	(0.002)
HZ_i	0.063***	0.032*	0.089**	0.052***	0.516**	0.070***	0.123***
	(0.014)	(0.017)	(0.042)	(0.012)	(0.205)	(0.016)	(0.005)
ENERGY							0.317***
							(0.013)
$\text{Log}(\text{POP/AREA}_{i,t-1})$	1.165***	0.805***	0.861***	0.837***	0.656**	1.370***	0.139***
	(0.207)	(0.220)	(0.249)	(0.097)	(0.297)	(0.256)	(0.037)
$\text{Log}(\text{AREA}_1)$	0.735***	1.071***	0.803***	0.824***	0.888***	1.370***	0.611***
	(0.098)	(0.145)	(0.179)	(0.063)	(0.230)	(0.185)	(0.010)
Constant	−31.941**	−61.575***	−37.860***	−27.270***	−68.965***	−59.855***	−59.663***
	(12.749)	(17.775)	(14.076)	(5.374)	(25.503)	(16.926)	(0.140)
Sample:	CY	DR	SL	FL	VO	EQ	EQ
Observations	4144	4144	4144	4144	4144	4144	93
Left Cens.	3649	4045	4107	3602	4126	3987	59
Pseudo R^2	0.0869	0.0998	0.124	0.153	0.109	0.179	0.246

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10% significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes. (6) ENERGY is multiplied by 10^{14}.

contrast this is not the case for floods and volcanoes. One may want to note that the data underlying the hazard calculation is particularly poor for flood events (see Dilley et al. (2005)).

Given that our analysis by disaster types consistently showed a lack of results in congruence with our multi-hazard analysis for floods and volcanoes we re-conducted our multi-hazard analysis excluding these two disaster types. The results of this are given in the final column of Table 2. Reassuringly, only considering windstorms, earthquakes, droughts, and landslides does not alter our overall conclusions regarding the interplay between economic losses, the level of development, and hazard exposure, although this does alter the size of these effects marginally.

Another concern may be with regard to the nature our sample. More specifically, by creating a panel of country loss data over time we are not only including years in which potential natural disasters translated into actual natural disasters and years in which potential natural disaster events did not cause enough damage to be considered a 'disaster', but also years in which neither such events took place. Moreover, we do not control for the scientific severity of the event when it does occur. If either the probability of a potential disaster event or the magnitude of the event are correlated with wealth, but not completely captured by our hazard variable, then our results may be biased. Of course, identifying potential disaster events and their magnitude would be a difficult if not impossible task for all disaster types included in our data. One exception in this regard are earthquakes, for which there are relatively accurate historical records to identify actual significant earthquake events, even if they did not translate into major natural disasters as captured by the EM-DAT database. In particular, the Significant Earthquakes Database maintained by the NOAA contains a listing of earthquakes over time if they resulted in ten or more deaths, moderate damage (approximately $1 million or more), a magnitude of at least 7.5 on the Richter Scale, or a Modified Mercalli Intensity of at least X. Additionally, the database includes a scientific measure of the actual magnitude of the earthquake in terms of its Richter scale.

To investigate whether the concerns regarding our sample and the lack of a measure of the intensity of events we focused on all earthquake event country observations in the Significant Earthquakes Database and re-ran Eq. (13) including the hazard interaction terms as well as a measure of the energy released as implied by the magnitude, where we weight the latter by the share of population within a country within a 50 km radius of the epicenter.[16] One should note that this reduced our sample to 93 data points, of which 59 were earthquake event years that did not, according to the EM-DAT database, result in economic losses. The results are given in the last column of Table 3. As can be seen, the energy of the earthquake is, as would be expected, positively related to the amount of economic losses. More importantly, our results concerning the loss–wealth relationship and the dependency of this on the hazard faced by a country, shown in the last column of Table 4, are qualitatively similar as in Column 6 of the same table, where we used our benchmark sample for earthquakes.

5. Conclusion

In this article we investigate the relationship between the losses from natural disasters, the exposure to different levels of natural hazard and the stages of economic development. Our main contributions are the analysis of this relationship via a theoretical model as well as through an econometric analysis of a cross country panel dataset. We find that both the theoretical model and the empirical analysis predict a non-linear relationship between economic losses and the stages of economic development and that this crucially depends on a country's hazard of natural disasters. More specifically, countries that face low or intermediate hazard have a bell-shaped relationship between economic losses and wealth; whereas countries that face high hazard have a u-shaped relationship between losses and wealth. This stands in contrast to the current literature, which has suggested losses either always decrease or, more recently, face an inverted u-shaped relationship with wealth.

Our results indicate that extreme care must be taken when modeling and analyzing the relationship between wealth and economic development. More specifically, there appears to be no simple 'increasing wealth–reducing losses' relationship, making policy recommendations that much harder. One primary prominent feature that comes out of our analysis is, however, that the exposure to natural disaster hazard is an important driving force behind any relationship between economic losses and wealth. In terms of policy suggestions, it seems therefore essential to generate and provide as much information as possible concerning likely current and future hazards of the different areas where people are living or planning to move to. This information is necessary for agents to properly adapt to the natural hazard situation and should therefore help prevent excessive losses.

[16] Energy released is measured in joules (divided by 10^{17}) as given by the scale at http://earthquake.usgs.gov/learning/faq.php?categoryID=2&faqID=33.

Table 4
Single hazard regressions — Interaction effect.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.:	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*	*LOSS*
$\text{Log}(\text{GDP/POP}_{i,t-1})$	5.950*	8.627*	6.429*	3.016*	12.776**	10.357**	19.231***
	(3.254)	(4.745)	(3.487)	(1.602)	(5.233)	(4.097)	(6.522)
$[\text{Log}(\text{GDP/POP}_{i,t-1})]^2$	−0.276	−0.489*	−0.336	−0.158	−0.721**	−0.566**	−1.061***
	(0.196)	(0.276)	(0.212)	(0.097)	(0.304)	(0.239)	(0.377)
HZ_i	2.106***	1.465	15.987***	0.116	55.856	3.278*	5.657***
	(0.566)	(1.308)	(5.777)	(0.530)	(42.528)	(1.940)	(1.833)
$\text{Log}(\text{GDP/POP}_{i,t-1})*\text{HZ}_i$	−0.501***	−0.406	−3.809***	−0.028	−12.871	−0.792*	−1.335***
	(0.140)	(0.331)	(1.371)	(0.129)	(10.048)	(0.458)	(0.422)
$[\text{Log}(\text{GDP/POP}_{i,t-1})]^2*\text{HZ}_i$	0.031***	0.028	0.227***	0.002	0.745	0.049*	0.080***
	(0.009)	(0.021)	(0.081)	(0.008)	(0.592)	(0.027)	(0.024)
ENERGY	–	–	–	–	–	–	0.356**
							(0.168)
$\text{Log}(\text{POP/AREA}_{i,t-1})$	1.152***	0.799***	0.904***	0.830***	0.663**	1.427***	0.252
	(0.212)	(0.209)	(0.240)	(0.098)	(0.300)	(0.260)	(0.301)
$\text{Log}(\text{AREA}_1)$	0.739***	1.060***	0.832***	0.813***	0.891***	1.393***	0.622**
	(0.102)	(0.138)	(0.183)	(0.064)	(0.233)	(0.191)	(0.282)
Constant	−42.401***	−61.014***	−45.399***	−26.279***	−75.136***	−67.103***	−93.942***
	(13.219)	(20.251)	(14.335)	(6.592)	(24.633)	(17.981)	(29.505)
Sample:	CY	DR	SL	FL	VO	EQ	EQ
Observations	4144	4144	4144	4144	4144	4144	93
Left Cens.	3649	4045	4107	3602	4126	3987	59
Pseudo R^2	0.0926	0.104	0.136	0.154	0.113	0.186	0.262

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10% significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes. (6) ENERGY is multiplied by 10^{14}.

Data Appendix. Outline of the Construction of a Multi-Hazard Risk Exposure Index by Dilley et al. (2005)

First, using the spatial grid schemata from the Gridded Population of the World (GPW) version 1 data set, the globe was divided into $2.5' \times 2.5'$ spatial units, resulting in about 8.7 million cells. Grid cells with less than five persons per kilometer were masked out since, while residents might be exposed to natural disasters, total casualties and/or losses are likely to be small. For the remaining cells indicators of hazard were then calculated separately for cyclones, droughts, earthquakes, floods, landslides, and volcanoes given available spatial data on probability, occurrence, and extent:

- o *Cyclones*: For cyclones storm track data covering the Atlantic, Pacific, and Indian Oceans over the period 1980–2000 was used in conjunction with a wind field model to calculate the wind speeds experienced within each grid cell. A measure of local hazard then consisted of considering the frequency as well as the wind strength of events.
- o *Droughts*: To calculate local measures of the hazard of droughts the weighted anomaly of standardized precipitation were computed for each grid cell from monthly rainfall data over the 21 year period. Drought events, from which the local hazard was constructed, were identified when a cell experienced a precipitation deficit was less than or equal to 50% of its long term median value for 3 or more consecutive months.
- o *Earthquakes*: For earthquakes information from both the local probabilistic estimate from the Global Seismic Hazard Program as well as actual earthquake events for the period 1976 to 2000 were utilized.

Table 5
Single hazard regressions — Alternative loss indicator.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*	*DEATH*
$\text{Log}(\text{GDP/POP}_{i,t-1})$	0.147**	0.286***	2.678*	0.037**	0.033	1.381*
	(0.059)	(0.105)	(1.489)	(0.015)	(0.023)	(0.823)
$[\text{Log}(\text{GDP/POP}_{i,t-1})]^2$	−0.008**	−0.017***	−0.198**	−0.002**	−0.002	−0.081*
	(0.003)	(0.006)	(0.099)	(0.001)	(0.001)	(0.048)
$\text{Log}(\text{POP/AREA}_{i,t-1})$	0.026***	0.023***	0.160***	0.004***	0.011***	0.041*
	(0.008)	(0.006)	(0.062)	(0.001)	(0.004)	(0.022)
$\text{Log}(\text{AREA}_1)$	0.018***	0.025***	0.191***	0.005***	0.011***	0.060*
	(0.005)	(0.007)	(0.071)	(0.001)	(0.004)	(0.031)
HZ_i	0.023**	0.083*	0.413*	0.079**	−0.003	5.247
	(0.010)	(0.049)	(0.224)	(0.033)	(0.005)	(3.877)
$\text{Log}(\text{GDP/POP}_{i,t-1})*\text{HZ}_i$	−0.005**	−0.020*	−0.110*	−0.019**	0.001	−1.238
	(0.002)	(0.011)	(0.058)	(0.008)	(0.001)	(0.922)
$[\text{Log}(\text{GDP/POP}_{i,t-1})]^2*\text{HZ}_i$	0.000**	0.001*	0.007**	0.001**	−0.000	0.073
	(0.000)	(0.001)	(0.004)	(0.000)	(0.000)	(0.055)
Constant	−0.909***	−1.543***	−12.709**	−0.221***	−0.287**	−6.901*
	(0.299)	(0.513)	(5.895)	(0.077)	(0.133)	(3.990)
Sample:	CY	EQ	DR	SL	FL	VO
Observations	4144	4144	4144	4144	4144	4144
Left Cens.	3503	3872	4108	3911	3263	4121
Pseudo R^2	0.963	0.903	0.191	−1.812	−0.635	0.482

Notes: (1) Standard errors in parentheses; (2) Time dummies included; (3) Robust standard errors allowing for within country clustering; (4) ***, **, and * are 1, 5, and 10% significance levels. (5) CY: cyclones; DR: droughts; EQ: earthquakes; FL: floods; LS: landslides; VO: volcanoes.

o *Floods*: Flood hazards measures were derived from the Dartmouth Flood Observatory database which provides information on the location and extent of major flood events across the globe since 1985.
o *Landslides*: As a measure of the probability of landslide disasters information was taken from the global landslide hazard map developed by the Norwegian Geotechnical Institute which is based on local slope, soil and soil moisture conditions, precipitation, seismicity, and temperature.
o *Volcanoes*: For volcanoes spatial coverage of volcanic activity from 79 A.D. through 2000 A.D. from the Worldwide Volcano Database served as the basis for the local hazard measure construction.

In order to arrive at a local summary measure of hazard for each disaster type each grid cell was grouped into global deciles according to the local hazard derived from the underlying data just described.[17] Each cell was then for each disaster type category weighted according to its decile in the global distribution on a 1 to 10 scale, where those in the top decile were given a value of 10, those in the second highest a value of 9 etc. Values of 8 and above were then summed over all disaster types to arrive at a multi-hazard summary measure at the grid cell level, necessarily ranging between 0 and 48.

Since the probability of total losses due to natural disasters will not only depend on the probability and scale of the incident but also on the potential local exposure, we follow the Dilley et al. (2005) and for each grid cell multiply the multi-hazard summary measure by their proposed index of local population density estimate based on the 2000 values from GPW data, which similarly consists of values ranging from 1 to 10 according to its global decile grouping. Thus this population density weighted multi-hazard index can feasibly range in value from 0 to 480.

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[17] For example, for cyclones the local hazard would have been calculated by translating wind speeds at the 1 km^2 scale into the Saffir Simpson Hurricane scale, and using these to calculate how often a grid cell is hit and what severity over the 21 year period.