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Normalizing economic loss from natural disasters: a global analysis

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Normalizing Economic Loss from Natural Disasters: A Global Analysis

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Abstract

Climate change is likely to lead to an increase in the frequency and/or intensity of certain types of natural hazards, if not globally, then at least in certain regions. All other things equal, this should lead to an increase in the economic toll from natural disasters over time. Yet, all other things are not equal since affected areas become wealthier over time and rational individuals and governments undertake defensive mitigation measures, which requires normalizing economic losses if one wishes to analyze trends in economic loss from natural disasters for detecting a potential climate change signal. In this article, we argue that the conventional methodology for normalizing economic loss is problematic since it normalizes for changes in wealth over time, but fails to normalize for differences in wealth across space at any given point of time. We introduce an alternative methodology that overcomes this problem in theory, but faces many more problems in its empirical application. Applying, therefore, both methods to the most comprehensive existing global dataset of natural disaster loss, in general we find no significant upward trends in normalized disaster damage over the period 1980 to 2009 globally, regionally, for specific disasters or for specific disasters in specific regions. Due to our inability to control for defensive mitigation measures, one cannot infer from our analysis that there have definitely not been more frequent and/or more intensive weather-related natural hazards over the study period already. Moreover, it may still be far too early to detect a trend if human-induced climate change has only just started and will gain momentum over time.

1. Introduction

Has economic damage from natural disasters increased over time? This is a question of high policy relevance for mainly two reasons. First, if it has then this could require a policy response in terms of disaster risk management and disaster damage mitigation and prevention. Second, an increasing trend of damage from natural disasters could point in the direction that climatic changes may be the driving force, which would have implications for the debate on reducing greenhouse gas emissions (Bouwer 2009; Schmidt, Kemfert and Höppe 2009).[1] This question has recently attracted some broader media attention when critics accused both the Intergovernmental Panel on Climate Change (IPCC) and the Stern (2007) Review of allegedly reporting selected pieces of evidence in support of such a trend.[2]

A potential climate change signal is not easily detected from data of economic loss from natural disasters, however. One cannot simply look at inflation-adjusted damages from natural disasters and test for a time trend therein. While such an analysis would be interesting for other reasons, any trend found may simply be due to the fact that areas affected by natural disasters have become wealthier over time. For example, people often move to disaster-prone areas such as floodplanes and coastal areas because other characteristics of these areas attract them, which provide a higher expected benefit than the expected cost following from damage in the uncertain event of natural disaster. Even in the absence of migration, existing populations in affected areas are bound to increase over time, while property values are bound to rise. Hence, any increase in natural disaster damage may be entirely due to an increase in what can potentially be destroyed, i.e. an increase in exposed wealth, rather than because of an

1 For example, IPCC (2001: 13) claims that ‘part of the observed upward trend in disaster losses over the past 50 years is linked to socioeconomic factors (…), and part is linked to climatic factors, such as the observed changes in precipitation and flooding events’.

2 See, for example, Pielke (2007).

increase in the frequency and/or intensity (potential destructive power) of natural hazards.[3] Even then, a policy response may be required of course – for example, in the form of discouraging people from migrating to disaster-prone areas and undertaking measures to protect the lives and property of existing people in such areas.

The question that has attracted more scholarly attention, however, is whether even after adjusting for changes in wealth, there is still an increasing trend in natural disaster damage over time. Certainly, if one is interested in analyzing whether climatic change plays a role in increasing disaster damage, then this is the question to address. Existing scholarship seemingly provides an exhaustive negative answer to this question already, but there is a large amount of terra incognita in terms of adequate regional- and hazard-specific loss analyses, partly because of unavailability of data. Existing scholarship comes to the conclusion that while natural variability in weather patterns can explain some of the variability in disaster losses (Pielke and Landsea 1998; Katz 2002; Pielke et al. 2008; Schmidt, Kemfert and Höppe 2009), there is no evidence for a rising long-term trend in so-called "normalized" disaster damage, which is the damage after adjustments for wealth changes over time. To be sure, even if a trend was detected, one needs to be careful in attributing such a trend to anthropogenic climate change, i.e. climate change caused by man-made greenhouse gas emissions, since natural climate variability could provide an alternative explanation. For example, some studies find an upward trend in normalized damage from hurricanes in the US since the 1970s (e.g., Schmidt, Kemfert and Höppe 2009) – a trend, which may well be explained by natural variability in hurricane landfall.

There are three reasons why the topic of natural disaster loss normalization needs to be studied further. First, the vast majority of existing studies have either

[3] Hazards are events triggered by natural forces. They will turn into natural disasters if people are exposed to the hazard and are not resilient to fully absorbing the impact without damage to life or property (Schwab, Eschelbach and Brower 2007).

analyzed losses in the United States (Pielke and Landsea 1998; Brooks and Doswell 2001; Nordhaus 2006; Pielke et al. 2008; Vranes and Pielke 2009; Schmidt, Kemfert and Höppe 2009) or other countries (Raghavan and Rajseh 2003; Crompton and McAeneney 2008) or a region (Pielke et al. 2003; Barredo 2009).[4] It remains to be seen whether what holds true for these individual countries or regions will hold for other countries, other regions and the world as a whole. Second, the one study that has looked at disaster damage on a global scale (Miller et al. 2008) suffers from the fact that it had to resort to assembling loss estimates from a plethora of sources, which will use very different criteria and which will produce data of very varied quality. Third, the normalization methodology used by practically all existing studies is, we argue here, incomplete in that it normalizes for changes over time, but fails to normalize for differences in spatial location at any point of time. This article addresses all three shortcomings by analyzing a global sample in addition to region-specific samples, by using a comprehensive high-quality database and by employing, in addition to the conventional method, a methodology that normalizes both for changes over time and differences over space. In other words, this article makes both a contribution to the substance and the methodology of the literature studying economic loss from natural disasters.

Despite these differences in research design, we come to similar conclusions as existing studies: whilst we find massive increases in non-normalized inflation-adjusted natural disaster damage, there is no longer any evidence for an increasing trend once each natural disaster event has been normalized. It is premature to interpret these findings as evidence that climatic factors have not led to an increase in normalized disaster damage. This is because defensive mitigating measures

[4] Bouwer (2009) provides a comprehensive literature review.

undertaken by rational individuals and governments in response to more frequent and/or more intensive natural hazards may have reduced natural disaster losses such that these measures would mask any increasing trend in normalized disaster damage. Unfortunately, it is impossible to adequately account for measures such as improved early warning systems, better building qualities, heightened flood defences etc. It is therefore impossible to say whether one would see an increasing trend in normalized natural disaster damages in the absence of such measures.

This article is structured as follows: Section 2 outlines the conventional approach to normalise disaster losses, while Section 3 discusses its limitations. Our alternative method is presented in Section 4. Results of a global analysis and for various regions and disaster types are shown in Section 5, using both normalization approaches. Section 6 concludes with an emphasis on the caveats and limitations that necessarily accompany our analysis. In particular, we stress that our inability to take into account defensive mitigating measures implies that one cannot infer from our analysis that there has been no actual increase in the frequency and/or intensity of weather-related natural hazards. Our analysis therefore cannot be used to undermine the case for reducing greenhouse gas emissions – based on the precautionary principle and justified in part by a desire to prevent or reduce a potentially increasing trend in economic loss from natural disasters in the future.

2. The conventional approach to normalizing natural disaster loss

The conventional approach to normalizing natural disaster loss can be credited to Roger Pielke Jr. and co-authors (see Pielke and Landsea 1998, Pielke et al. 1999, 2003, 2008; Vraines and Pielke 2009). The typical equation to compute normalized damage according to this approach is as follows:

$$Normalized\ Damage_t^s = Damage_t \cdot \frac{GDPdeflator_s}{GDPdeflator_t} \cdot \frac{Population_s}{Population_t} \cdot \frac{Wealth\ per\ capita_s}{Wealth\ per\ capita_t} \quad (1)$$

where *s* is the (chosen) year one wishes to normalize to, *t* is the year in which damage occurred, the Gross Domestic Product (GDP) deflator adjusts for inflation (i.e., change in producer prices), while the remaining two correction factors adjust for *changes in* population and wealth per capita. In theory, the population and wealth changes should be based on data from the exact areas affected by the natural disaster in question. However, in practice it is often impossible to determine the exact areas or information on these areas is difficult or impossible to get, so scholars typically resort to using data from the country or, if they can, from sub-country administrative units known to be affected (e.g., counties or states). Studies differ with respect to how wealth per capita is measured. Some use data on the value of capital stocks (e.g., Pielke and Landsea 1998; Brooks and Doswell 2001; Vranes and Pielke 2009; Schmidt, Kemfert and Höppe 2009) or the value of dwellings (Crompton and McAneney 2008; Pielke et al. 2008), others, often for lack of data, simply GDP per capita (e.g., Raghavan and Rajseh 2003; Pielke et al. 2003; Nordhaus 2006; Miller et al. 2008; Barredo 2009). With more than one disaster per year, the measure of disaster loss per year is the sum of normalized damages from each disaster as per equation (1).

Pielke et al. (2008) justify the conventional normalization approach to disaster losses by saying that it provides “longitudinally consistent estimates of the economic damage” that past disasters would have caused “under contemporary levels of population and development”. Normalization thus accounts for the fact that, even after adjusting for inflation, actual damage from disasters in the past, when affected areas were less populous and less wealthy, is typically smaller in absolute terms than actual damage from contemporaneous disasters. It therefore adjusts past disaster damage for wealth and population changes to make them comparable to absolute contemporaneous disaster damage. In other words, past disasters would have caused higher damage had they hit the same areas as back then nowadays and normalization accounts for the fact that most places have become more populous and wealthier over time.

3. Problems with the conventional normalization approach

The problem with conventional normalization is that it is incomplete. It adjusts for changes in wealth and population over time, but fails to adjust for differences in wealth and population across space at any given point of time. Conventional normalization correctly posits that a disaster like the 1926 Great Miami hurricane would have caused far more damage if it hit Miami nowadays since the value of what can potentially become destroyed has increased tremendously over this time period (Pielke et al. 1999). At the same time, however, a hurricane that hits Miami in any year will cause a much larger damage than a hurricane that hits in the same year rural parts of Florida with much lower population density and concentration of wealth. Conventional normalization accounts for the former effect, but not for the latter. It makes Miami in 1926 comparable to Miami in 2010, but fails to make Miami in whatever year comparable to rural Florida or other areas affected by a particular natural disaster in that same year.

The incompleteness of conventional normalization means that it is not a fully valid measure of disaster loss for the purpose of detecting a trend in disaster loss over time. In order to be a valid measure for this purpose, a normalization method must fulfil the following two conditions:

a. Ceteris paribus, normalized loss in period 1 must be higher than normalized loss in period 0 if more disasters of the same intensity strike in period 1: higher frequency leads to higher loss.

b. Ceteris paribus, normalized loss in period 1 must be higher than normalized loss in period 0 if the same number of disasters strike in period 1 with higher intensity: higher intensity leads to higher loss.

Conventional normalization is not guaranteed to fulfil either condition. If more disasters of the same intensity or the same number of disasters with higher intensity strike less wealthy areas in period 1 than in period 0, then the conventionally normalized loss from period 0 may well be higher than the loss in period 1, even in the absence of any growth in wealth between period 0 and 1 (the ceteris paribus assumption). By measuring absolute loss rather than relative loss (relative to what can potentially be destroyed), conventional normalization fails to provide a valid measure of disaster loss.

Will the failure to account for relative loss (relative to what can potentially be destroyed) represent a problem for conventional normalization in detecting a trend? In its defence, one could argue that contrary to temporal changes in wealth and population for which one is bound to observe more wealth and population in later compared to earlier periods due to population and economic growth, there is no reason why one would expect that disasters *systematically* hit more populous or wealthier areas relatively more than less populous or less wealthy areas in either earlier or later periods. Invoking the law of large numbers, one could therefore argue that normalization does not need to account for differences in spatial location since with a very large number of disasters such differences in spatial location will cancel each other out in an analysis of trends in the aggregated sum of disaster loss over time: disasters will sometimes hit poor and low population density areas and sometimes hit wealthy and high population areas, but with a very large number of disasters the expected damage, normalized according to conventional methodology, is the same in early as in later parts of the study period – much the same as with many throws of a dice or many tosses of a coin the expected average dice count will be 3.5, while the expected probability of heads will be 50%. However, depending on what type of disaster (low or high frequency), what unit of aggregation (sub-country units, country, region, global) and what length of study period one looks at, there may well be too few relevant disasters to invoke the law of large numbers. Also, if one is interested in disaster loss more generally, i.e. going beyond mere trend analysis over time, then one needs to account for differences across spatial location to make a meaningful comparison of relative disaster loss. If, for example, one wants to know whether natural disasters cause relatively more damage in one part of a country, region or the world than in another, then conventional normalization is obviously unsuitable.

4. An alternative normalization method

The upshot of the discussion in the previous section is that if one wants to make disaster losses that occur in different spatial locations and different time periods comparable, then one needs to normalize for differences in both space and time. In order to do so, we have developed another normalization approach that does exactly this. Our normalization equation is specified as follows:

$$Normalized\ Damage_t = \frac{Damage_t}{Wealth_t}\ , \qquad (2)$$

In way of explanation, first note that the population correction factor of the conventional methodology is in fact redundant if one were to use in equation (1) a correction factor for wealth rather than wealth per capita, since the sum of the change in population and the change in wealth per capita equals the change in wealth. Hence, by using wealth rather than wealth per capita in equation (2), we do not need to account for population. Second, by dividing damage in year *t* by wealth in year *t* rather than multiplying it with a correction factor $\frac{Wealth_s}{Wealth_t}$ as per conventional methodology, our normalization method does not normalize absolute damage values. Rather, it expresses damages from any time period as relative damages, namely as a relative loss of total wealth in affected areas, which is theoretically bounded below by zero (no damage) and above by one (total loss of all wealth). Equation (2) can therefore be interpreted as an actual-to-potential-loss (APLR) ratio. With more than one disaster per year, our aggregate measure of disaster loss per year is the sum of APLRs of any given year. As argued below, this provides a valid measure of disaster loss, where validity is defined as per the previous section.

Because equation (2) measures relative rather than absolute loss, we do not need to scale up or down absolute damages from different points of time to arrive at normalized absolute damages as per conventional methodology. For the same reason, we do not need to adjust for inflation, since damage relative to wealth is a ratio, which is not subject to inflation distortion, as long as one divides either nominal damage by nominal wealth in year *t* or damage expressed in constant prices of a given year by wealth in prices of the same year. Lastly, note that relative damage normalization as per equation (2) does not require the choice of a base year *s* to which damages are normalized to as per conventional method of equation (1).[5]

It should be clear why, contrary to conventional methodology, our competing normalization equation adjusts for differences across spatial location: by dividing actual damage by the wealth in affected areas that can potentially be destroyed we adjust for the fact that the same natural disaster will necessarily create more absolute damage if it strikes a wealthier area than if it stroke a poorer area where there is less potential wealth to be destroyed. But what about adjusting for differences over time? By expressing normalized damage as damage in relation to wealth, no further adjustment for differences in wealth over time are needed as relative damage is time-invariant and therefore directly comparable across time. An example may advance understanding of this crucial point. The 1926 Great Miami hurricane would have created a much larger absolute damage than the absolute damage recorded at the time were this hurricane to hit Miami in, say, 2010 instead and, following conventional methodology, the absolute damage therefore needs to be scaled up in order to make it comparable to absolute damages in 2010. Our normalization approach instead normalizes each damage by the wealth that could have potentially been destroyed at the time and by expressing each damage in the same invariant unit (the APLR, i.e. ratio of actual to potential loss), no scaling up of previous disaster damages are required. Absolute damages are not comparable over time and therefore need adjustment along the lines of conventional methodology, but relative damages are directly comparable over time and need no further adjustment.

Our proposed alternative normalization method is theoretically superior to conventional normalization because it fulfils both conditions for a valid measure of

[5] This is not an advantage of our methodology over conventional methodology since the choice of a normalization 'base' year has no substantive implication. We merely mention it to facilitate understanding.

natural disaster loss, as defined in section 3. The sum of APLRs will be higher in period 1 than in period 0 if, ceteris paribus, more disasters of the same intensity strike in period 1 or if, ceteris paribus, the same number of disasters strike with higher intensity in period 1. The first contingency would lead to more APLRs of the same size to be added up to the aggregate sum of APLRs of period 1, while the second contingency would lead to the same number of APLRs, but of larger size, to be added up to the aggregate sum of APLRs of period 1.

5. Empirical analysis of trends in disaster losses

5.1 The Research Design

Our period of study covers the years 1980 to 2009. In principle, estimates of loss from natural disasters exist before 1980, but it is only since 1980 that these are systematically, comprehensively and consistently included in Munich Re's NatCat database (Munich Re, personal communication). The disadvantage of not being able to use data from further back in time is that, ceteris paribus, the shorter the time series of annual loss data the less likely any trend will be detected as statistically significant (the smaller N, the number of observations, the higher the standard error of the estimate). Also, the IPCC (2007a: 942) defines climate in a narrow sense "as the average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities" over a period of 20 to 30 years, so our time period of 30 years may be too short to identify changes in climate.

The NatCat database provides high quality data, but it is of course not perfect. Economic damage is always estimated. Smaller disasters may be somewhat under-reported in the early periods relative to later periods. This would slightly bias the analysis toward finding a significant upward trend in disaster loss, which we do not find in our empirical analysis below. At MunchRe, several members of staff scan daily international and regional sources to compile information about disaster events. Data on economic loss and victims are collected from a variety of sources including government representatives, relief organisations and research facilities. Information on economic losses, however, is also based on insurance claims to MunichRe's customers, which provide the best approximation to the actual damage. Initial reports on fatalities and losses, which are usually available in the immediate aftermath of a disaster, are often highly unreliable. Therefore, data in the NatCat database is updated continuously as more accurate information becomes available, which might be even years after the disaster event. 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.

For two reasons, we employ both conventional normalization methodology and our proposed alternative. First, we wish to compare the results of the two methodologies. Second, and more importantly, while we contend that our proposed alternative methodology is theoretically superior to conventional normalization, it faces many more problems in its empirical operationalization than conventional normalization, particularly if applied at the global level.

The empirical problems with the theoretically correct measure of natural disasters loss from equation (2) all have to do with accurately measuring the wealth that can potentially be destroyed by a natural disaster, i.e. with the denominator in equation (2). The first problem is that there typically are no good measures of wealth available, particularly for a global analysis. We therefore need to use a proxy for wealth, which in our case is gross domestic product (GDP). GDP has the advantage that it captures well potential economic loss due to the interruption of economic operations as a result of a natural disaster, but it is a relatively poor proxy for the physical wealth stock potentially destroyable by disasters. Whereas economic wealth is a stock, GDP is a flow of economic activity. Fortunately, despite GDP consisting in part of intangible components such as services with scant correspondence to the value of the physical wealth stock, on the whole GDP is highly correlated with it. But GDP can only function as a proxy for wealth and typically understates it. Economists estimate the ratio of the value of the physical man-made or manufactured capital stock to GDP to lie somewhere in between 2 and 4 for a typical macro-economy (D'Adda and Scorcu 2003). But this ratio will differ from country to country and, more importantly, is a national macro-economic average, which can differ more drastically across sub-country units.[6] It also only captures the value of the physical capital stock used for the production of consumption goods and services, but not the value of other wealth held in the form of, for example, residential property. Moreover, the increasing share of GDP consisting of intangible components such as services, which is observed in many, but not all, countries implies that the growth rate of GDP possibly over-estimates the growth rate of the physical wealth stock. This will bias the results against finding a positive trend since disasters from past periods are scaled up too strongly as a result of normalization.

The second problem stems from defining the area potentially affected by a natural disaster, which determines the boundaries of wealth (or GDP) to be included in the denominator of equation (2). Few natural disasters affect an entire country such that the country's total GDP could be taken as the proxy for potential wealth to be

[6] It has also changed over time (see D'Adda and Scorcu 2003), but Krugman (1992: 54f.) concludes that "there is a remarkable constancy of the capital-output ratio across countries; there is also a fairly stable capital-output ratio in advanced nations. These constancies have been well known for a long time and were in fact at the heart of the famous Solow conclusion that technological change, not capital accumulation, is the source of most growth."

destroyed. Disasters are more likely to affect a smaller area. The problem is that it is very difficult to know the exact affected area for each natural disaster. In our analysis, we resort to the extreme simplifying assumption that each disaster affects an equally sized area of 100 x 100 kilometres, i.e. 10,000 square kilometres arranged equally around the reported centre of the disaster. This introduces some measurement error and, potentially, some bias.[7] In future research, we will tackle this issue and we will attempt to measure the affected area more adequately contingent on specific natural disasters and/or specific countries or regions looked at.

Readers will wonder why these empirical problems do not equally affect conventional normalization methodology. The answer is that they do affect conventional methodology, but differently and arguably less so. Conventional normalization also suffers from, depending on the unit of analysis and the quality of available data, having to resort to proxy measures of wealth and not knowing the exact affected areas. But since conventional normalization only adjusts for *changes in* wealth over time, rather than *levels of* wealth across time and space, it suffers less from these problems. The assumption that growth in GDP is a good approximation for growth in wealth in all areas affected by natural disasters is less restrictive than the assumption that the GDP to wealth ratio is the same in all affected areas. Similarly, if conventional normalization does not capture the true affected area, but takes some

[7] The measurement error could be non-random (i.e. systematically under- or overestimating the true affected area relatively more in earlier or later periods), but is more likely to be random. It could be non-random if, for example, one is willing to make the assumption that climate change leads to larger areas being affected over time such that our approximation would tend to under-estimate the affected area relatively more in later compared to earlier periods. Since this would lead us to over-estimate normalized damage in later periods and we mostly fail to find significant upward trends in normalized damage, we are not much concerned about this specific type of non-random measurement error. Random measurement error will lead to attenuation bias of the estimated coefficient toward zero and thus will make it less likely that we will find a statistically significant trend. A similar problem plagues the conventional normalization method, however. Its failure to account for spatial heterogeneity introduces a kind of measurement error. Even when this is random measurement error, the analysis will be somewhat biased against finding a significant trend. This caveat should be kept in mind when interpreting the findings of this and previous studies.

proxy thereof, then the error this introduces derives from the fact that the change in wealth in the truly affected area can be different from the change in wealth in the area assumed to be affected. The bias in growth rates is likely to be much smaller than the bias in absolute levels of wealth, which is the relevant bias for our proposed alternative normalization approach.

In sum, while normalization according to equation (2) is theoretically superior to normalization according to equation (1), our proposed alternative faces many more problems in empirical operationalization. We therefore regard it as complementary to conventional normalization, definitely not as a substitute. If both normalization methods lead to similar results, then we can be more confident in the results.

In the remainder of this section, we describe our empirical research design in more detail. For the results generated with our alternative method, the starting point is GDP data taken from the G-Econ project (G-Econ 2010), which provides worldwide information on GDP in purchasing power parity, on a one degree latitude/one degree longitude resolution. GDP data in purchasing power parity is preferable to GDP estimates at exchange rates known to under-state GDP in poorer countries. Data is available for 1990, 1995, 2000, and 2005. The dataset, developed by Nordhaus et al. (2006) builds on previously established data for the gridded population of the world and contains a cell-level equivalent to GDP. Data comes from various sources at different levels of spatial disaggregation, such as regional GDP information, regional income and employment by industry, or regional urban and rural population or employment along with sectoral data on agricultural and non-agricultural incomes. If regional data is not available, as is the case for many of the lowest-income countries particularly in Africa, spatial distribution of population is taken to impute a spatial

GDP distribution (Nordhaus et al. 2006). To create gridded data, information is then spatially rescaled from political boundaries to geophysical boundaries.

In a first step, we filled the gaps in time by intra-polation assuming a constant growth rate. We then extrapolated the values backwards to 1980 and forward to 2009, based on country growth rates, adjusted for differences in cell-level growth rates to account for the fact that some regions, for instance urban centers, grow at a faster pace than others. For backward extrapolation, we average annual country growth rates with the cell growth rate between 1990 and 1995, while for forward extrapolation we average annual country growth rates with the cell growth rate between 2000 and 2005. As a consequence, cells that grew faster than the country average between 1990 and 1995 are also assumed to have grown faster than the country as a whole between 1980 and 1989, while cells that grew faster than the country average between 2000 and 2005 are also assumed to grow faster than average after 2005 to 2009.

With increasing distance from the equator, the size of a one degree longitude/one degree latitude cell decreases. To correct for this, all cells are rescaled to a cell size of 100 x 100 kilometres, i.e. 10,000 square kilometres, leaving the proportion of land mass in each cell unchanged. This is equivalent to modelling a quadrangular world. Under the assumption of an equal distribution of GDP within a cell, we then divided each cell into nine subcells of the same size. For the largest number of events, the NatCat database provides a geo-reference of the centre of the disaster. The affected area of an event is taken to have the size of nine subcells, which is equal to the original size of one cell.[8] How the subcells are chosen depends on where the centre of the disaster lies with respect to the gridded GDP-cells. Figure 1a illustrates an example on the Northern hemisphere east of the zero meridian, in which

[8] While we have tested for the effect of assuming different sizes of affected areas and found results to be robust, in future research, we will adjust the size of the assumed affected area, making it contingent on the type of natural disaster analyzed.

the centre of the disaster is in the North-Eastern subcell of a one degree latitude/one degree longitude cell. We calculated the affected area as the sum of four subcells in the cell in which the disaster took place, plus two subcells of the cell adjacent in the North, one subcell of the cell in the North-East, and two subcells of the cell in the East. In 11.7 percent of the cases the geo-reference lies on the intersection of one degree latitude and one degree longitude, which might be due to data inaccuracy. As illustrated in Figure 1b, in these cases the affected area is simply the sum of the four adjacent cells divided by four. Consequently, a quarter of the affected area comes from each of the four adjacent cells in these cases.

Since GDP data provided by G-Econ (2010) is in constant 1995 international dollar we deflated the disaster losses to year 1995 values, which are expressed in nominal USD in NatCat, using the US GDP deflator. The normalized damage is then calculated by dividing the deflated losses by the GDP of the affected area. This gives the APLR for each disaster. Note that these APLRs are not bound from above by one because GDP is only a proxy of wealth, which often will be several times larger than GDP. Out of 19,360 disasters for which we have APLRs, 204 are above one. However, in a very few cases we arrive at implausibly high APLRs where the loss in relation to the assumed affected area is far too large to be plausible. In these cases, the centre of disaster is usually located in a very sparsely populated area or on a small island. This might indicate a coding error in the geo-referencing. In addition, wide-ranging disasters such as droughts and wildfires are over-represented in the list of disasters with top APLRs. For such disasters, it is hard to identify the centre and the assumed affected area might be much smaller than the truly affected area. We decided to drop 20 (out of 19,360) disasters with an APLR over 50. While this choice is somewhat arbitrary, our results are not affected by choosing a lower threshold.[9] They also remain valid if we do not exclude these events from the analysis.

To arrive at the annual aggregate,[10] the sum of APLRs of disasters happening in one year is taken.[11] To test for the existence of a trend, the time-variant sum of APLRs from each year is regressed on a linear year variable and an intercept:

$$[\text{Annual sum of APLRs}]_t = \alpha_0 + \beta_1 \text{year}_t + \varepsilon_t \qquad (3)$$

A trend is statistically significant if the null hypothesis that β_1 is equal to zero can be rejected at the ten percent level or lower. From a statistical point of view, this approach is potentially problematic, but we found the results to be robust to alternative approaches.[12]

For the conventional normalization approach, we normalised disaster losses to 2009 values by multiplying the original disaster damage, which is expressed in nominal USD in NatCat, with three multipliers each accounting for the change in producer price levels (using the US GDP deflator), as well as the changes in the country's population and GDP per capita in purchasing power parity, respectively. We use country level data for population and GDP from World Bank (2010). To test

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9 We tested various cut-off levels down to an APLR of more than 1.5.

10 Scholars so far have typically aggregated damage figures to annual aggregates. However, it is not clear that annual aggregates are necessarily more appropriate than, say, monthly aggregates. We repeated our analysis using monthly aggregates and generally found no more evidence for increasing trends than with the annual aggregates.

11 We took the onset of a disaster as the relevant information for the year of occurrence. Most disasters are short-lived.

12 To understand why from a statistical point of view the approach taken is potentially problematic, note that the APLRs consist of the ratio of two rather random variables, the loss and the associated gross cell product (GCP) value, and the distribution of the annual sum of APLRs is likely to have a so-called "fat tail". In our context, these fat tails appear, for example, if a disaster hits a very sparsely populated area with a very low GCP in the denominator. A consequence of fat tail distributed data series is that the trend detection power of common statistical tests might be low because a weak trend signal could be drowned out by the highly volatile fat tail data. As an alternative to our method, one can compensate for very large and very small APLR-outliers by summing the total disaster losses and the total affected GCP per year before calculating the ratio. This alternative measure mitigates the problem of heavy tails but comes at the cost of being a pure intensity measure as it neglects disaster frequency. We found no more evidence for significant trends in normalized disaster loss using this alternative to our preferred method, but we will tackle in more detail the question of the trend detecting power of different normalization methods in future research.

for the existence of a trend, the annual sum of normalized disaster losses from each year is regressed on a linear year variable and an intercept:

$$[\text{Annual sum of damage}]_t^{2009} = \alpha_0 + \beta_1 \text{year}_t + \varepsilon_t \qquad (4)$$

As before, a trend is statistically significant if the null hypothesis that β_1 is equal to zero can be rejected at the ten percent level or lower. Robust standard errors are employed in all estimations.

5.2 Results

We start by showing *non-normalized* natural disaster loss at the global level, where loss is merely adjusted for inflation (see figure 2). There is a clear and statistically significant upward trend.[13] The question is: does this finding uphold if disaster loss is normalized?

Figure 3 shows loss from all natural disasters at the global level once normalized according to the conventional method and once normalized according to the alternative method. Whereas figure 2 covers all natural disasters, we lose some disasters (roughly 6 per cent) when normalizing loss due to lack of data.[14] To ensure comparability when contrasting results, the same sample is used for both normalization approaches. The graphs look somewhat different, as one would expect given the differences in underlying methodology. Normalized according to conventional method, there is no statistically significant trend, whereas there is a

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13 The coefficient and t-value of β_1 in equation (3) and the corresponding p-value are displayed at the bottom of each figure. Due to the devastating hurricane Katrina, which hit densely populated and wealthy areas on the South East coast of the USA in August 2005, this year shows extraordinarily high inflation-adjusted losses. Since this outlier is toward the end of the observed period, it could pivot the trend line upwards and inflate the significance of the trend. However, if we drop the year 2005, then the coefficient drops to 2.79, but the trend remains statistically significant at the five percent level (p-value: 0.012).

14 Figure 2 looks similar and the significantly positive trend remains if we restrict the sample of disasters to the ones for which we undertake normalization.

downward trend, significant at the 10 per cent level, according to the alternative method.

For the purpose of detecting a climate change signal, it makes no sense to include loss from all natural disasters since some disaster types will be practically unaffected by climate change. In figure 4, we therefore have taken out geophysical disasters (earthquakes, land slides, rock falls, subsidence, volcanic eruptions, and tsunamis) and only include the following disaster types: blizzards, hail storms, lightning, local windstorms, sandstorms, tropical cyclones, severe storms, tornados, winter storms, avalanches, flash floods, general floods, storm surges, cold and heat waves, droughts, winter damages, and wildfires. Both methods lead to the same result as for all disasters: no significant trend over time according to conventional method, a marginally significant downward trend according to the alternative method. If the very small number of disasters with very large APLRs above 50 are kept in the sample, the negative trend loses its significance (p-value of 0.115).

Climate change will not affect all regions or countries at different stages of development equally and in the same way. In figures 5a to 5f we therefore look at developed vis-à-vis developing countries as well as at specific regions of the world, employing the same list of weather-related disasters as in figure 4. Looking at developed nations first (figure 5a), no significant trend is found with the conventional approach, but a relatively strong negative trend, which is statistically significant at the one percent level, is found using the alternative method.[15] In contrast, the analysis yields no significant trends using either method for developing countries (figure 5b). This could possibly indicate a stronger capability of richer nations to fund defensive

[15] Interestingly, while hurricane Katrina is the major reason for conventionally normalized loss in 2005 to represent the largest loss in developed countries over the period 1980 to 2009, the sum of APLRs for 2005 is not even in the top three over this period. The reason is that while Katrina caused a very large economic loss, it also hit a relatively wealthy part of the developed world.

mitigating measures, which decrease vulnerability to natural disasters over time. As shown in figure 5c, the negative and significant trend is prevalent when normalizing with the alternative method for the US and Canada.[16] For all other selected regions, namely Western Europe (figure 5d), Latin America and the Caribbean (figure 5e), as well as South and East Asia and Pacific countries (figure 5f), no statistically significant trend is found under either approach.

Climate change also need not affect all climate-related disasters equally and in the same way. In figures 6a to 6d we therefore look at specific disaster types at the global level. For convective events (figure 6a), that is, damages from flash floods, hail storms, tempest storms, tornados, and lightning, there is no statistically significant trend, according to either normalization approaches. The same result is found for storm events (figure 6b) and for tropical cyclones (figure 6c). For precipitation-related events (figure 6d), we find no trend with the conventional approach, but a negative trend with the alternative method, which is significant at the ten percent level.

There is concern about specific climate-related disasters affecting specific regions, which is not sufficiently addressed by any of the analysis reported above. In figures 7a to 7d, we therefore look at specific disaster events in specific regions or countries. To begin with, Figure 7a displays disaster losses from convective events in the US. For the United States, data quality in the NatCat dataset is high also for earlier years back to 1970. We therefore are able to cover 40 years in this analysis. If losses are normalized according to the conventional method, a positive and statistically significant trend can be established. With the alternative method, however, the positive trend is marginally insignificant (p-value of 0.129). For the same disaster type in Europe, on the other hand, no significant trend is discernible after

[16] The trend remains statistically significant at the five percent level if the large value in the year 1984 is excluded.

normalization with either approach (figure 7b). Disaster losses caused by hurricanes in the US and in the Central American and Caribbean region have been subject to various focussed studies (Pielke and Landsea 1998, Pielke et al. 2003, Nordhaus 2006, Pielke et al. 2008).[17] We do not find a significant trend either in the United States (figure 7c) or in Central America and the Caribbean (figure 7d), independent of the normalisation approach applied. At face value, the result for the US contradicts studies, which have found an upward trend in US hurricane losses since the 1970s (e.g,, Schmidt, Kemfert and Höppe 2009). Note, however, that the trend with the conventional normalization approach is not too far from statistical significance (p-value of 0.166).[18]

6. Defensive mitigating measures

One of the problems with normalizing damage from natural disasters, independently of the method chosen, is our inability to take into account defensive mitigating measures, which rational individuals would undertake in response to an increasing frequency and/or intensity of natural hazards. An increase in such measures could prevent an increasing trend in natural disaster loss that would otherwise occur in the absence of such measures and could thus prevent detection of a potential climate change signal in the data. For example, flood defence measures in Western Europe have dramatically reduced the risk of flood damages from winter storms (e.g., Lavery and Donovan (2005) on the River Thames tidal defences or Ronde et al. (2003) on flood defence development in the Netherlands), while stricter building codes introduced in parts of coastal Florida from the mid-1990s onwards have significantly

17 Nordhaus (2006) finds a positive and significant trend in normalised tropical cyclone losses in the United States.

18 Moreover, if we restrict our analysis to the exact same time period as Schmidt, Kemfert and Höppe (2009) and regress, as they do, the log of normalized loss (rather than loss itself) on years, then we also find a significant trend.

reduced hurricane damage from Hurricane Charley in 2004 (Institute for Business and Home Safety 2008). Our findings of a downward trend in natural disaster loss with the alternative method for all natural disasters and for all non-geophysical disasters at the global level could be driven by such measures. Splitting up the sample into developed versus developing countries, we find a strong and more clearly statistically significant downward trend for developed countries, but no trend whatsoever for developing countries. This would also be consistent with increased defensive mitigating measures since developed countries are much better able to fund such measures than developing countries. To be sure, increased mitigating measures are only one possible explanation for the findings, but not the only one.

With the possible exception of Crompton and McAneney (2008) who study one specific type of natural disaster in one single country, due to lack of data no existing study has been able to adequately take defensive mitigating measures into account, and neither can we. Instead, we offer evidence on trends in the frequency of natural disasters, which could tentatively point in the direction that such measures are increasingly undertaken. To this effect, figure 8 shows trends in the simple count of disasters, once for weather-related and once for geophysical disasters not related to weather. There seems to be a clear upward trend in the frequency count of weather-related disasters. There is also an upward trend in the frequency count of geophysical disasters. However, the trend line for weather-related disaster counts suggests more than a doubling over the period 1980 to 2009, whereas the trend line for geophysical disasters suggests only a small percentage increase over this period. A natural question is whether this strongly increasing trend in the frequency count of weather-related disasters is driven by increased awareness and reporting of natural disasters in later compared to earlier periods as well as by new settlements in areas that were uninhabited before as populations and economies grow and where the same natural hazard would have gone unrecorded (no damage) before. To check this, in figure 9 we repeat the exercise from figure 8, but this time restricting the analysis to major disasters, for which a reporting bias is less likely. Major disasters are defined as disasters that exceed a property damage value, which is linearly interpolated from 85 million USD in 1980 to 200 million USD in 2009, or exceed a (time-invariant) fatality level of 100 people killed. As before, there is a clear upward trend in the frequency count of major weather-related disasters, but there is also an upward trend in the count of major geophysical disasters. As before, the frequency count of weather-related disasters increases relatively more than the frequency count of geophysical disasters. However, since there is no physical reason why the frequency count of major geophysical disasters should have increased, some reporting bias is likely to remain present even for major disasters, unless the increase can be fully explained by there being fewer uninhabited areas available in later periods. It is impossible to say how large this reporting bias is, but there could well be some increase in the frequency of weather-related disasters beyond what can be explained by reporting bias. Interestingly, one observes a similar upward trend in the frequency of weather-related disasters, both all and major ones only, for a country like Germany, in which reporting bias is not very likely and where no major expansion of population into previously unsettled areas has taken place over the period of our study (no figures shown, but available upon request).

Independently of the reason behind the strong increase in the frequency count of weather-related disasters over our period of analysis, how can this be reconciled with our finding of no upward trend in normalized damage from natural disasters? There are three possibilities. First, there could be an opposite reporting bias in terms of damage caused such that economic loss is over-estimated in the early years of our study period and under-estimated in the later years. Second, weather-related natural disasters could have become less intensive over time. Third, weather-related natural disasters have not become less intensive, but defensive mitigating measures have prevented increasingly frequent weather-related natural disasters from causing an upward trend in normalized natural disaster loss. Since there is little reason to presume that loss has been systematically over-estimated in the past or that weather-related natural disasters have become less intensive, the third explanation presents a distinct possibility.

7. Conclusion

In this article, we have analyzed whether one can detect an increasing trend in historical data on economic damage from natural disasters. We have argued that the conventional method used for normalization is theoretically problematic as it fails to normalize for a spatially heterogeneous distribution of wealth which renders absolute losses from different locations non-comparable to each other. We have proposed an alternative method, which normalizes disaster loss for both differences in space and time. The actual-to-potential loss (APLR) ratio provides a theoretically correct and valid normalization method for economic disaster loss. Contrary to conventional normalization, our proposed alternative is valid for the purpose of detecting a climate signal in the sense that it will always attribute a higher value to periods in which, ceteris paribus, more disasters of the same intensity take place or the same number of disasters strike with higher intensity. Yet, our theoretically correct measure of disaster loss encounters many more practical difficulties than the conventional normalization method, particularly if applied at the global level. We have therefore undertaken our analysis with both methods, regarding them as complements, not substitutes.

Independently of the method used, we find no significant upward trend in normalized disaster loss. This holds true whether we include all disasters or take out the ones unlikely to be affected by a changing climate. It also holds true if we step away from a global analysis and look at specific regions or step away from pooling all disaster types and look at specific types of disaster instead or combine these two sets of dis-aggregated analysis.

Much caution is required in correctly interpreting these findings. What the results tell us is that, based on historical data, there is no evidence so far that climate change has increased the normalized economic loss from natural disasters. More cannot be inferred from the data. In particular, one cannot infer from our analysis that there have not been more frequent and/or more intensive weather-related natural disasters.[19] Our analysis necessarily cannot take into account defensive mitigating measures undertaken by rational individuals and governments and a serious attempt at trying to collect data on such measures should top the priority list for future research. Such measures would translate into lower economic damage compared to the damage in the absence of defensive mitigation and if mitigating measures have increased and strengthened over time then this increasing trend toward mitigation could well mask an increasing trend in natural disaster loss over time. Our finding of an increasing trend in the frequency count of weather-related disasters, including only major ones, tentatively points in the direction of an increasing trend toward such defensive mitigating measures, unless the trend were fully explained by reporting bias. Besides the issue of defensive mitigating measures, another caveat to keep in mind in making

[19] In fact, our frequency count of weather-related natural disasters suggests increasing rather than decreasing frequency of such disasters.

inferences from our analysis is that it is based on historical data. Available evidence suggests that climatic change has only just begun and that it will take many years and decades still before its consequences will be truly felt (IPCC 2007a, 2007b). If so, the past will be a poor guide to the future.

In sum, while we find no evidence for an increasing trend in normalized economic damage from natural disasters, this provides no reason for complacency. That inflation-adjusted non-normalized disaster damage is significantly increasing should prompt policy-makers into seriously considering measures to prevent the further accumulation of wealth in disaster-prone areas. More importantly for the debate on climate change, our results do not undermine the argument of those who, based on the precautionary principle, call for reducing greenhouse gas emissions in order to prevent or reduce a potentially increasing economic toll from natural disasters in the future. We find no evidence for an increasing trend in the normalized economic toll from natural disasters based on historical data, but given our inability to control for defensive mitigating measures we cannot rule out its existence, let alone rule out the possibility of an increasing trend in the future.

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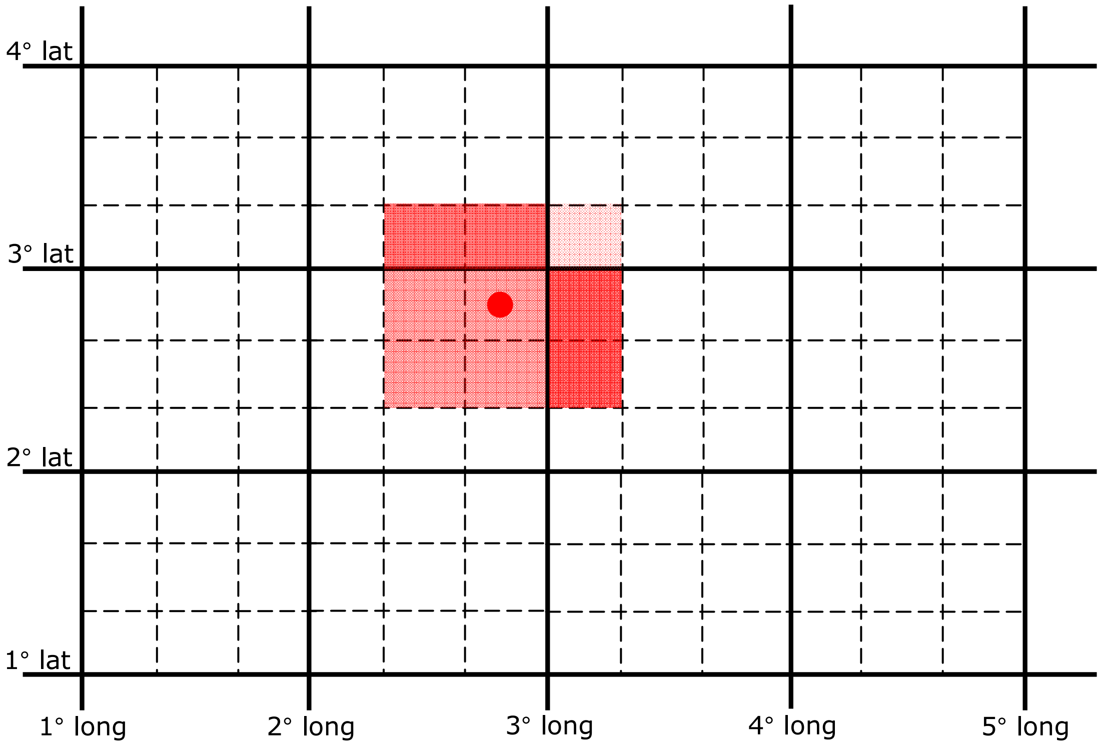
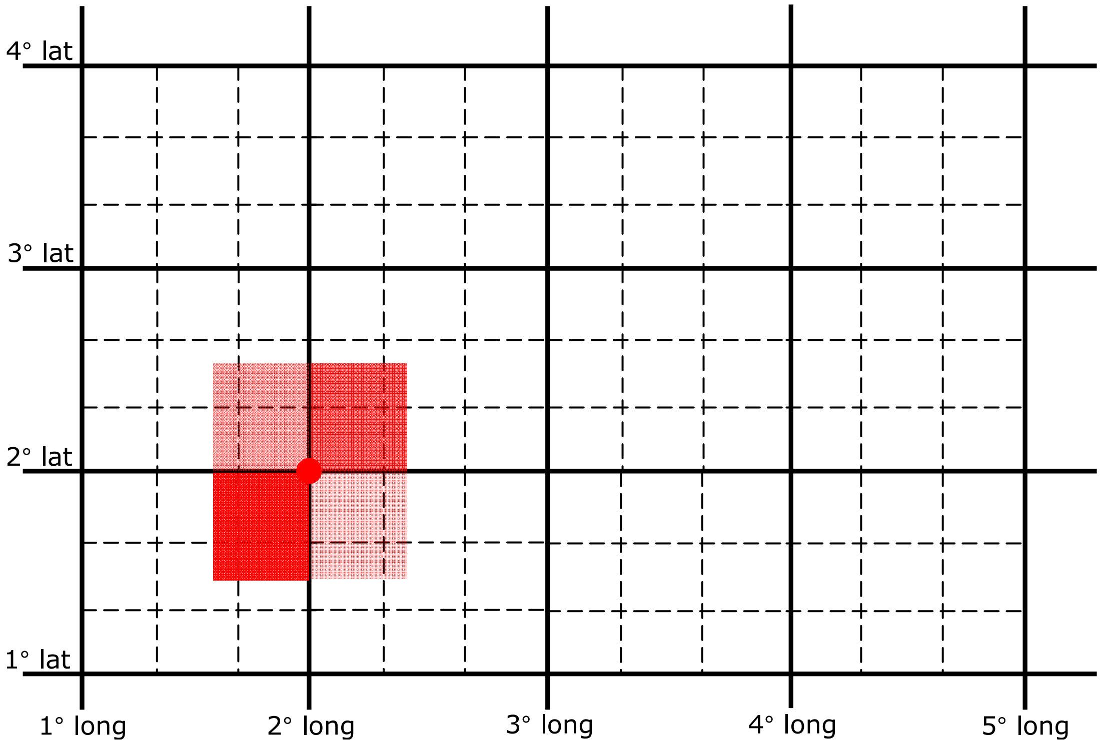
Figure 1a: Determining the affected area.



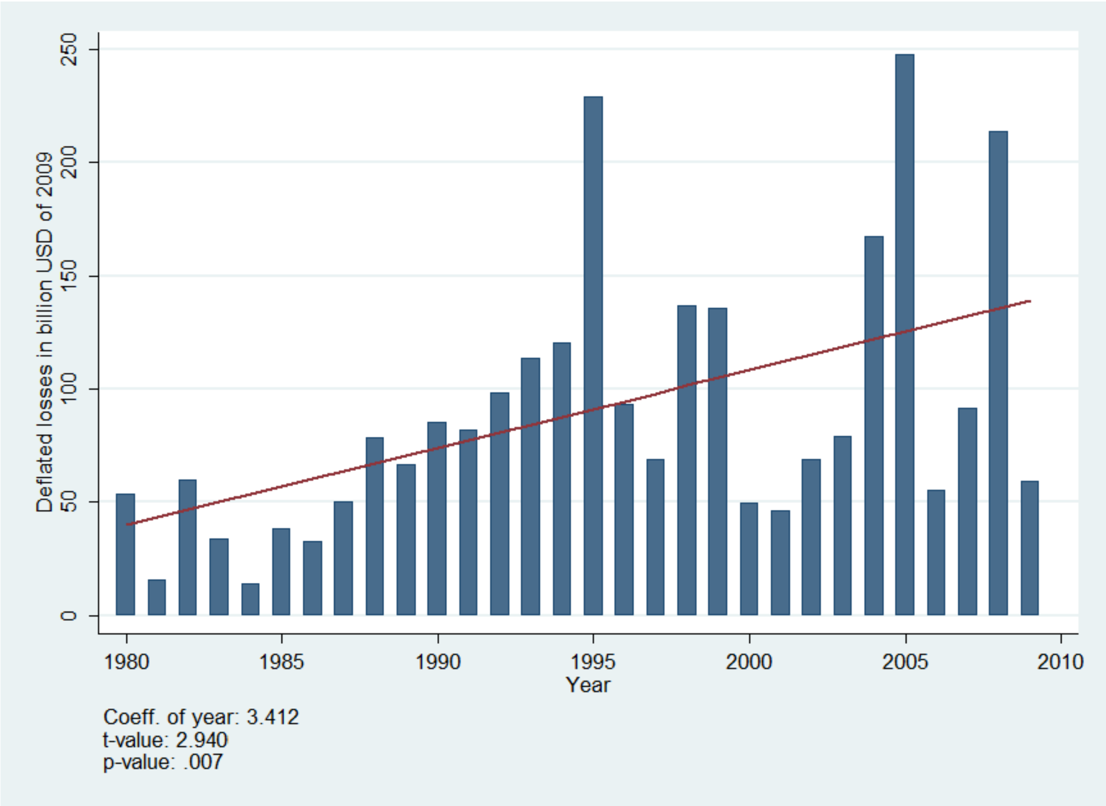
Note: Example shows the situation on the Northern hemisphere east of the zero meridian; Dot shows the geo-reference of disaster centre; different shades represent different levels of GDP.

Figure 1b: Determining the affected area if disaster centre is on the intersection of a degree of longitude and a degree of latitude



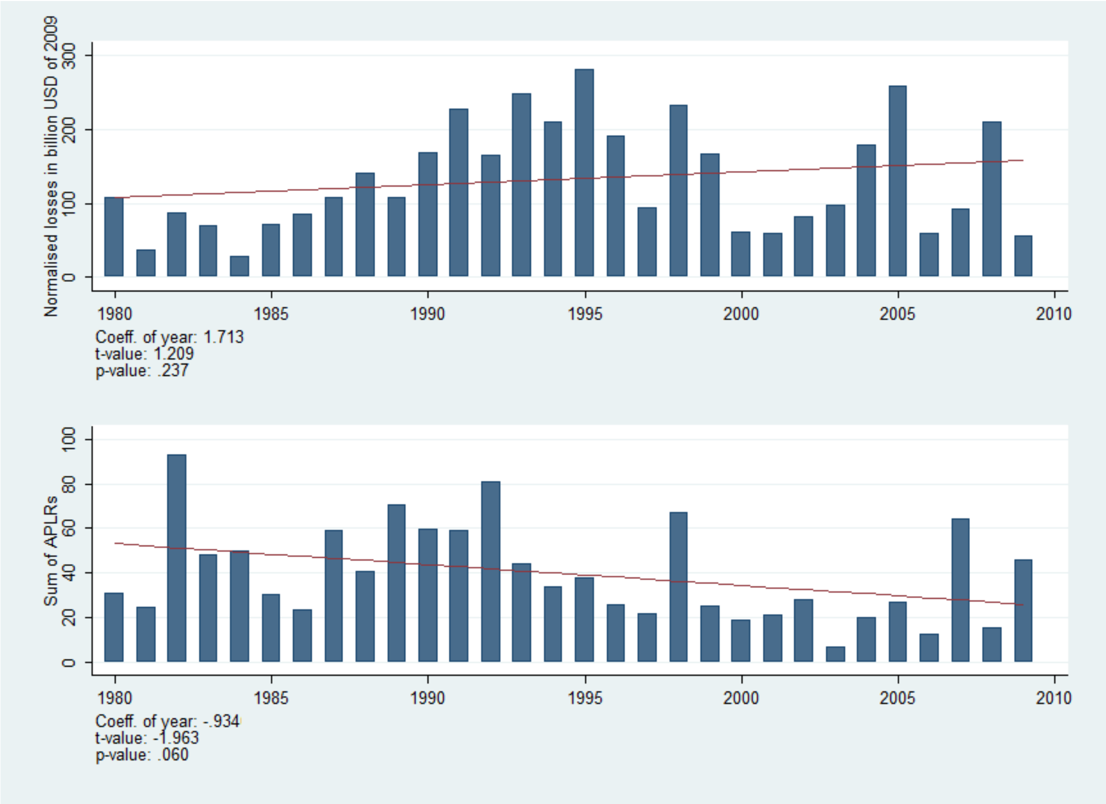
Note: Example shows the situation on the Northern hemisphere east of the zero meridian; Dot shows the geo-reference of disaster centre; different shades represent different levels of GDP.

Figure 2: Global deflated losses from natural disasters



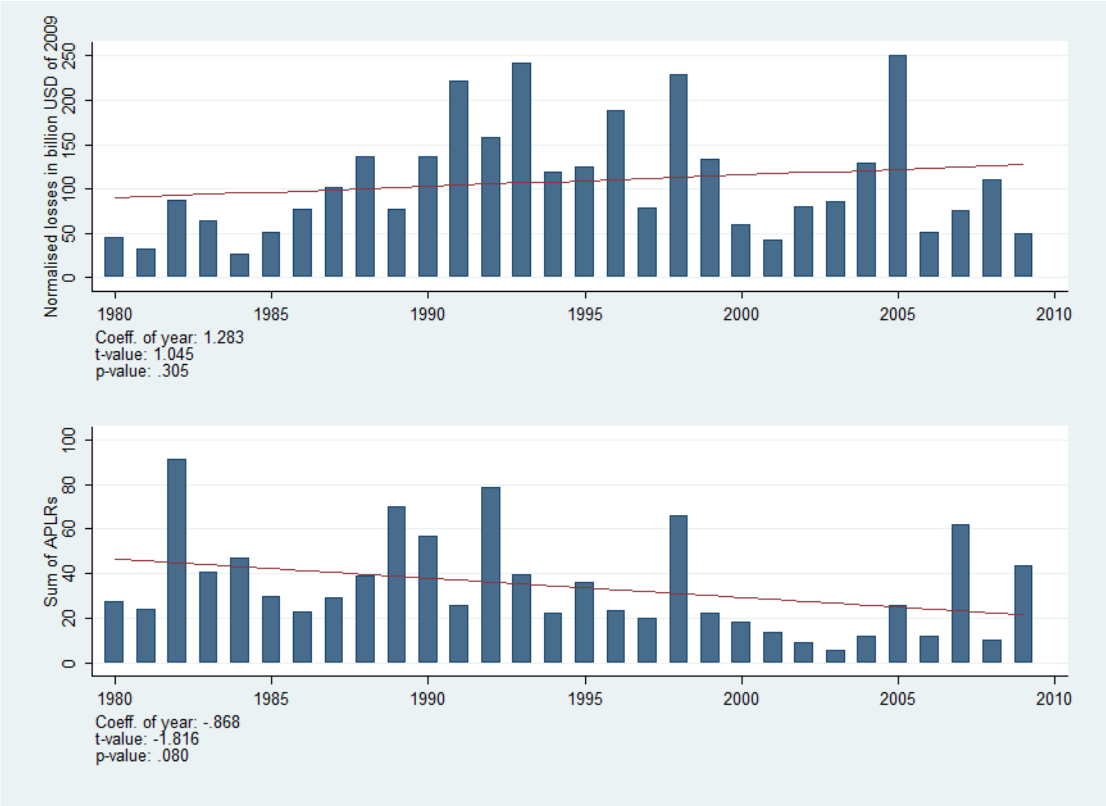
Note: Based on 20,375 disasters.

Figure 3: Global losses from all natural disasters normalized with conventional approach (top) and alternative approach (bottom)



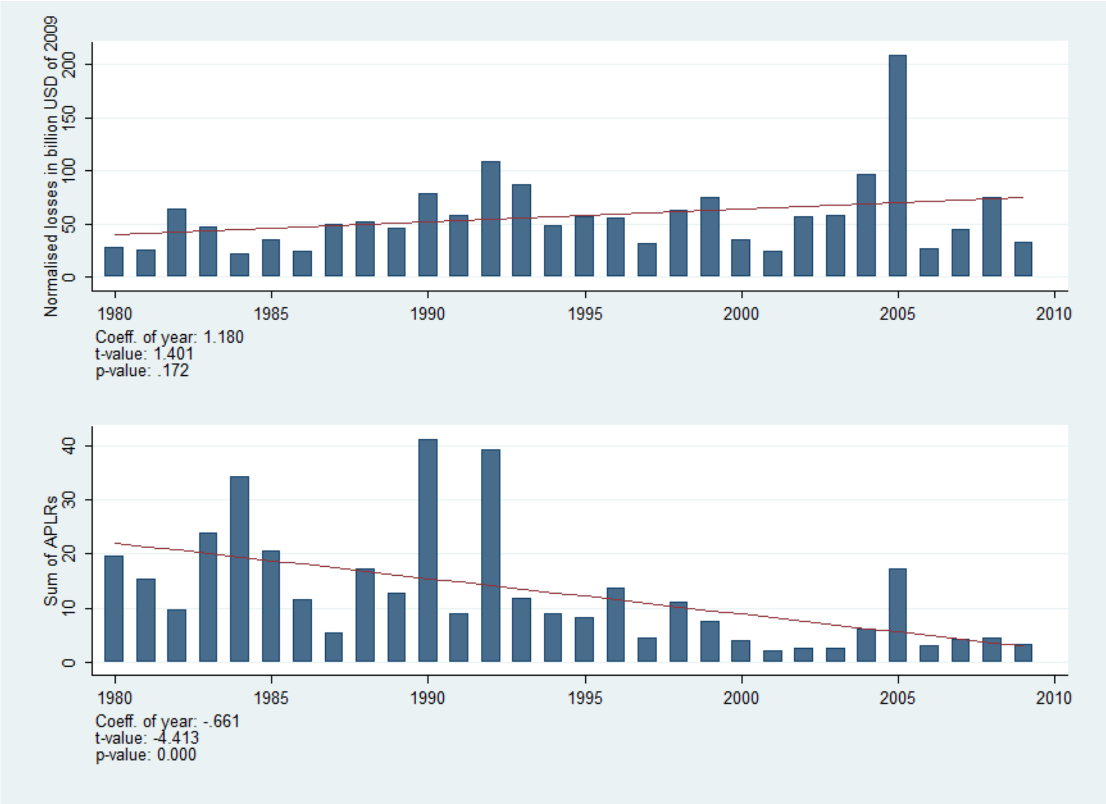
Note: Based on 19,115 disasters.

Figure 4: Global losses from non-geophysical disasters normalized with conventional approach (top) and alternative approach (bottom)



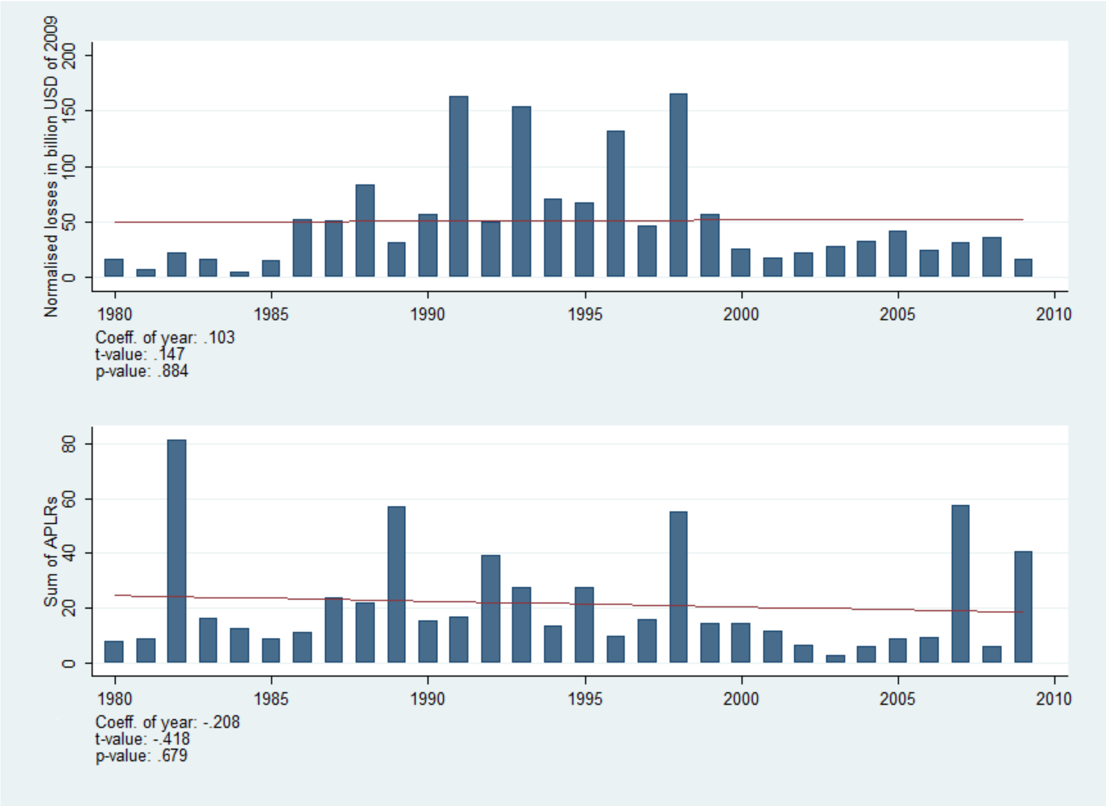
Note: Based on 16,645 disasters.

Figure 5a: Losses from non-geophysical disasters in developed countries normalized with conventional approach (top) and alternative approach (bottom)



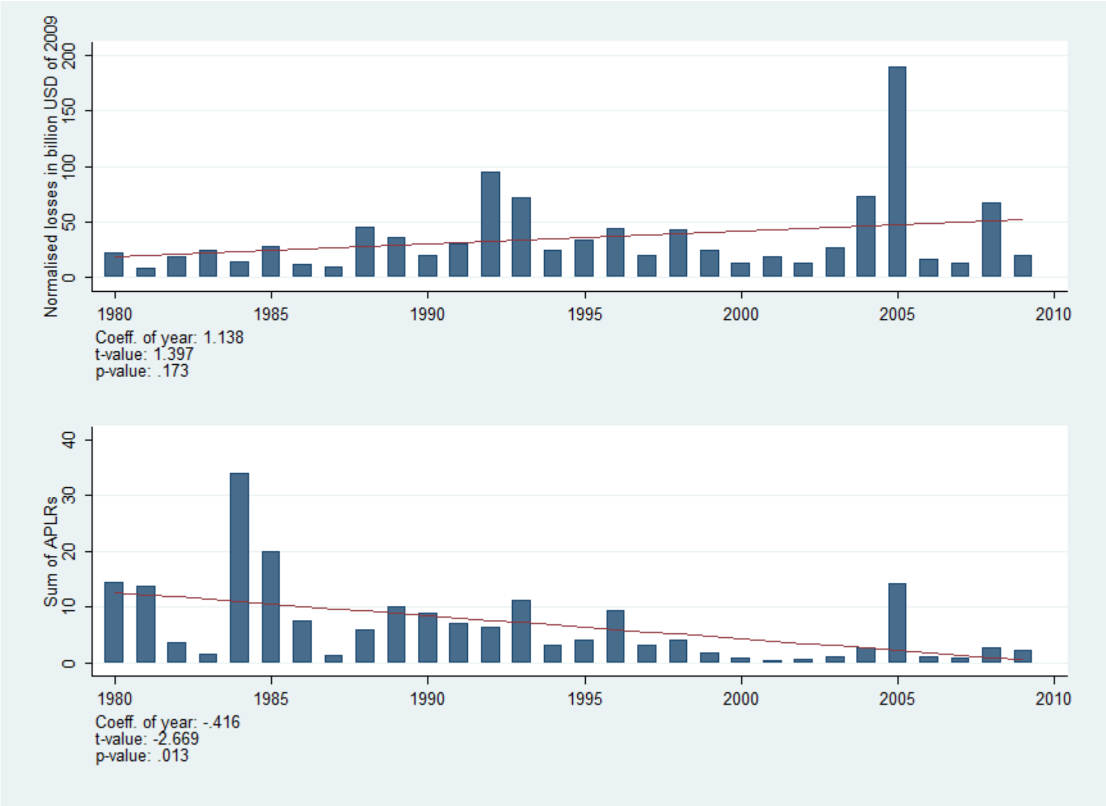
Note: Based on 8,307 disasters; developed countries cover OECD countries and other high-income countries according to World Bank classification.

Figure 5b: Losses from non-geophysical disasters in developing countries normalized with conventional approach (top) and alternative approach (bottom)



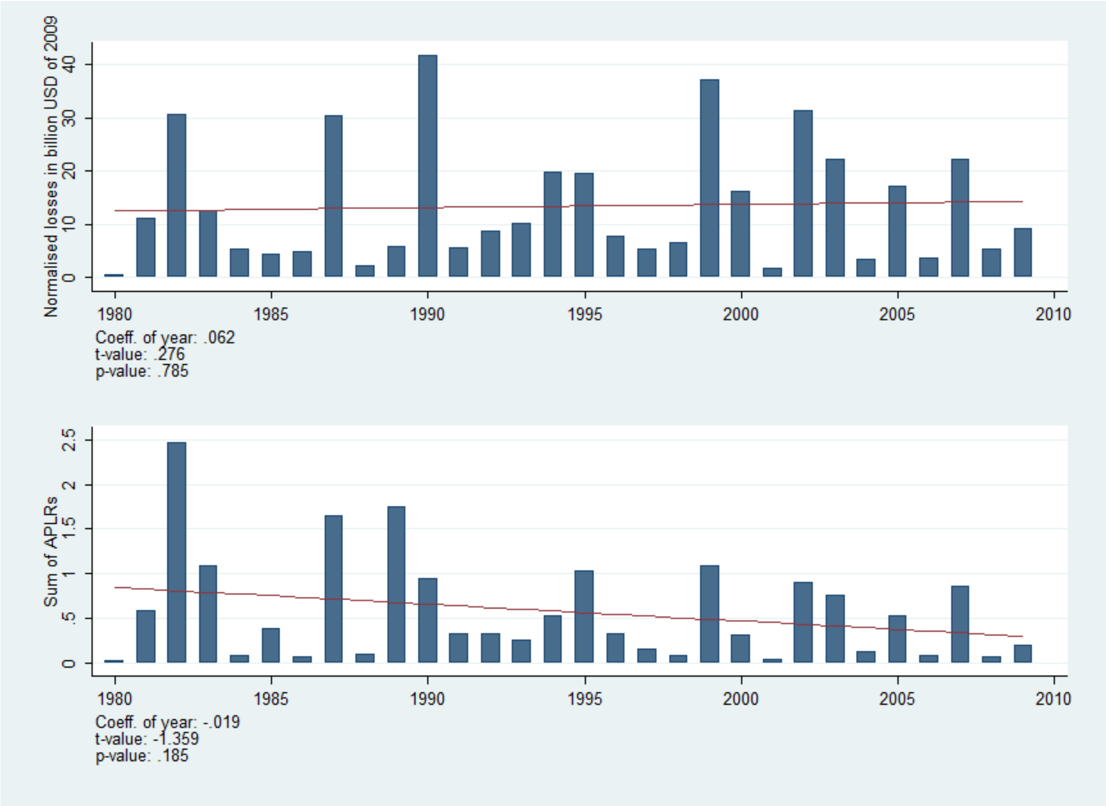
Note: Based on 8,338 disasters; Developing countries cover middle- and low-income countries according to World Bank classification.

Figure 5c: Losses from non-geophysical disasters in USA and Canada normalized with conventional approach (top) and alternative approach (bottom)



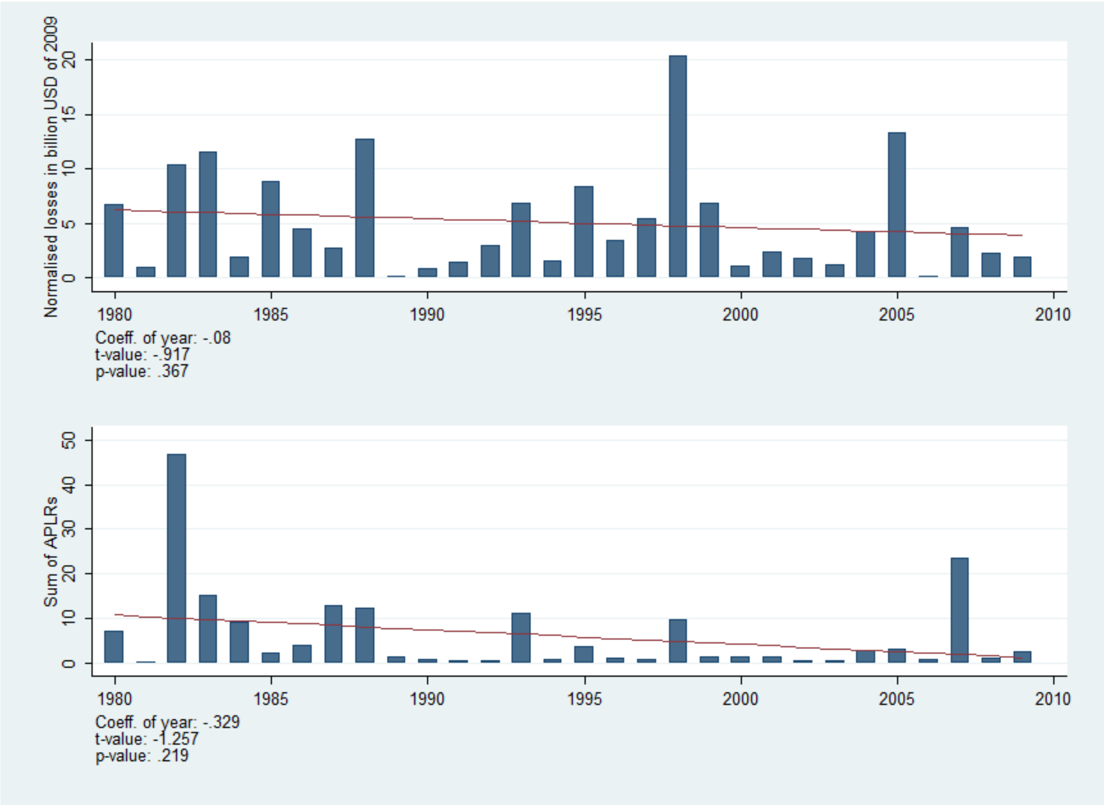
Note: Based on 3,240 disasters.

Figure 5d: Losses from non-geophysical disasters in Western Europe normalized with conventional approach (top) and alternative approach (bottom)



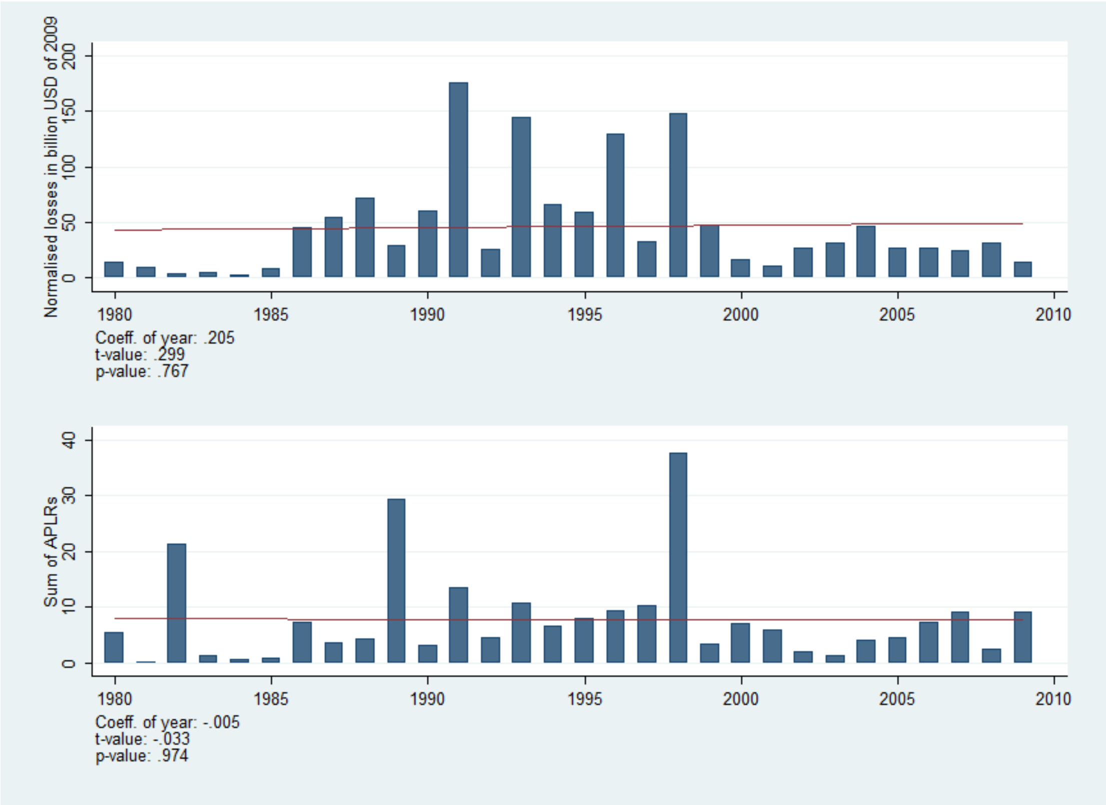
Note: Based on 3,319 disasters.

Figure 5e: Losses from non-geophysical disasters in Latin America and The Caribbean normalized with conventional approach (top) and alternative approach (bottom)



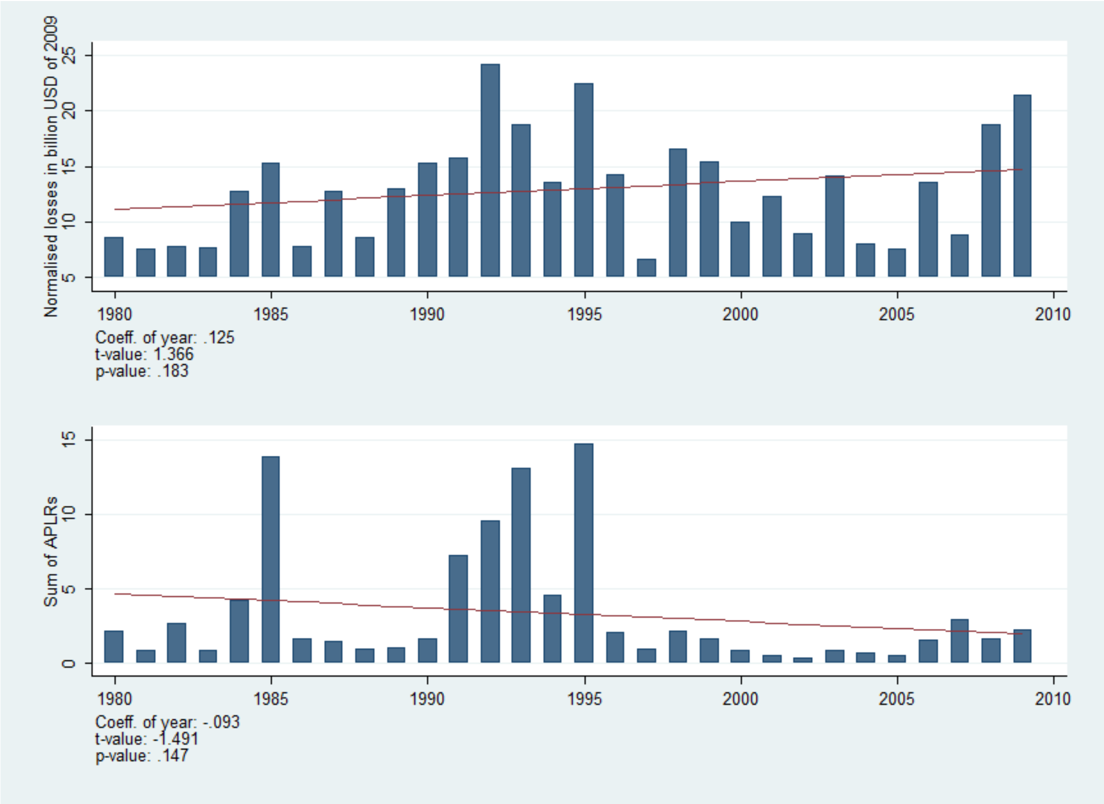
Note: Based on 1,795 disasters.

5f: Losses from non-geophysical disasters in South and East Asian and in Pacific countries normalized with conventional approach (top) and alternative approach (bottom)



Note: Based on 3,858 disasters.

Figure 6a: Global disaster losses from convective events normalized with conventional approach (top) and alternative approach (bottom)

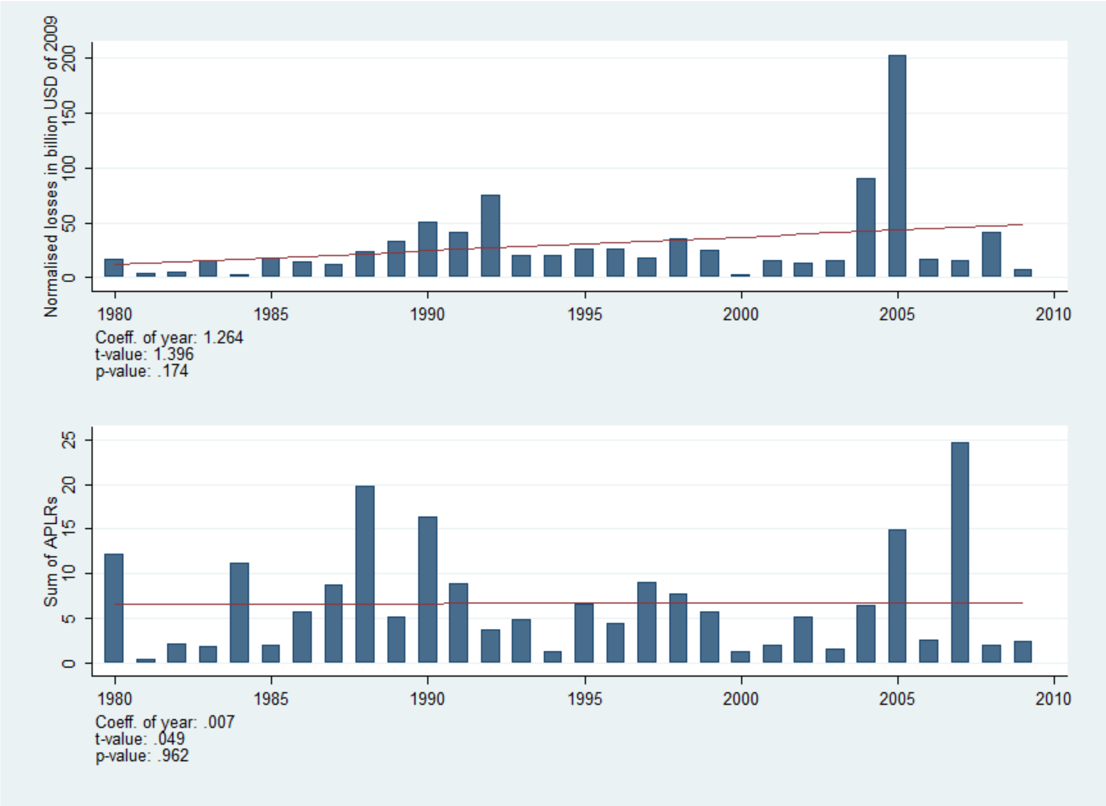


Note: Based on 5,869 disasters; Includes damages from flash floods, hail storms, tempest storms, tornados, and lightning.

Figure 6b: Global disaster losses from storm events normalized with conventional approach (top) and alternative approach (bottom)

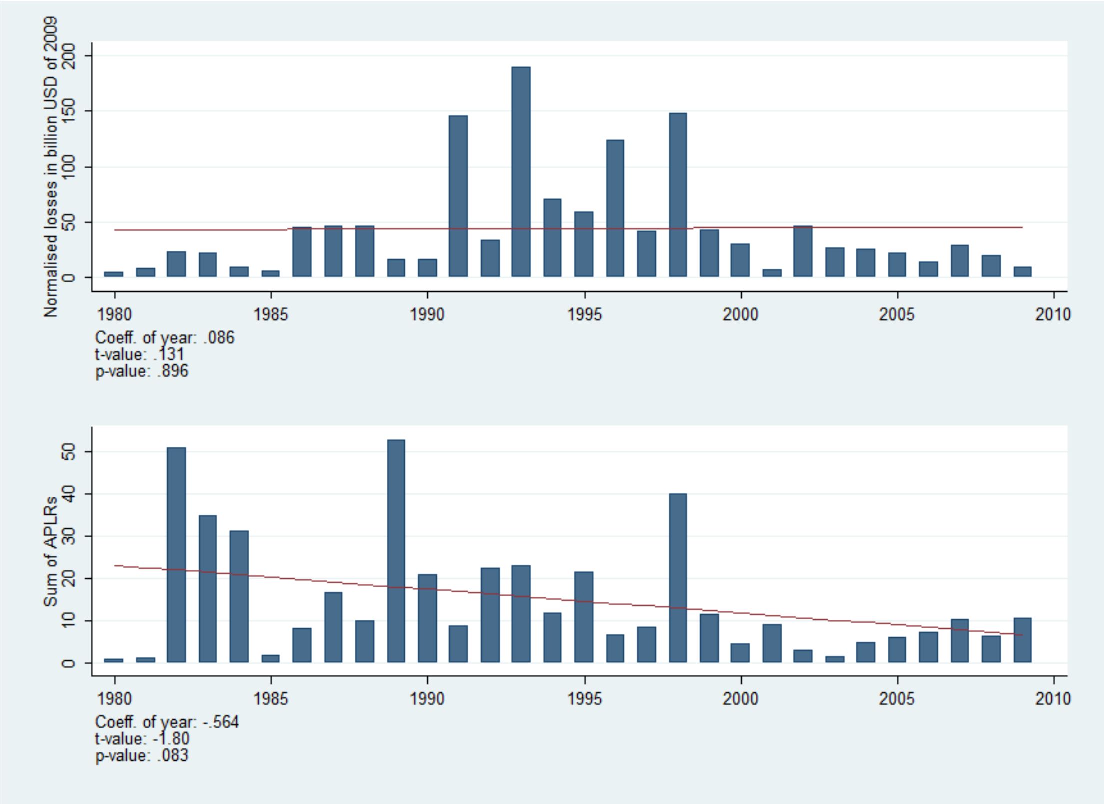
Note: Based on 6,179 disasters; Includes damages from winter storms (winter storm and blizzard/ snow storm), convective storms (hail storm, tempest storm, tornado, and lightning), sand storms, local windstorms, and storm surges.

Figure 6c: Global disaster losses from tropical cyclones normalized with conventional approach (top) and alternative approach (bottom)



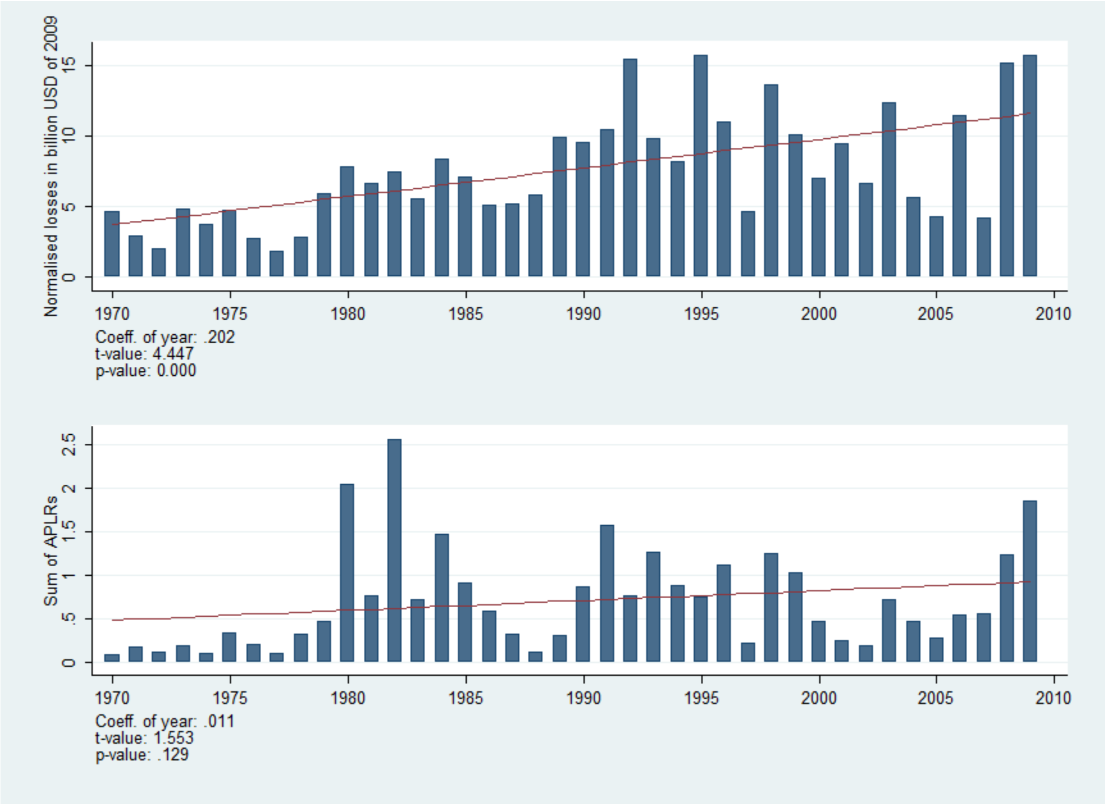
Note: Based on 1,456 disasters.

Figure 6d: Global disaster losses from precipitation-related events normalized with conventional approach (top) and alternative approach (bottom)



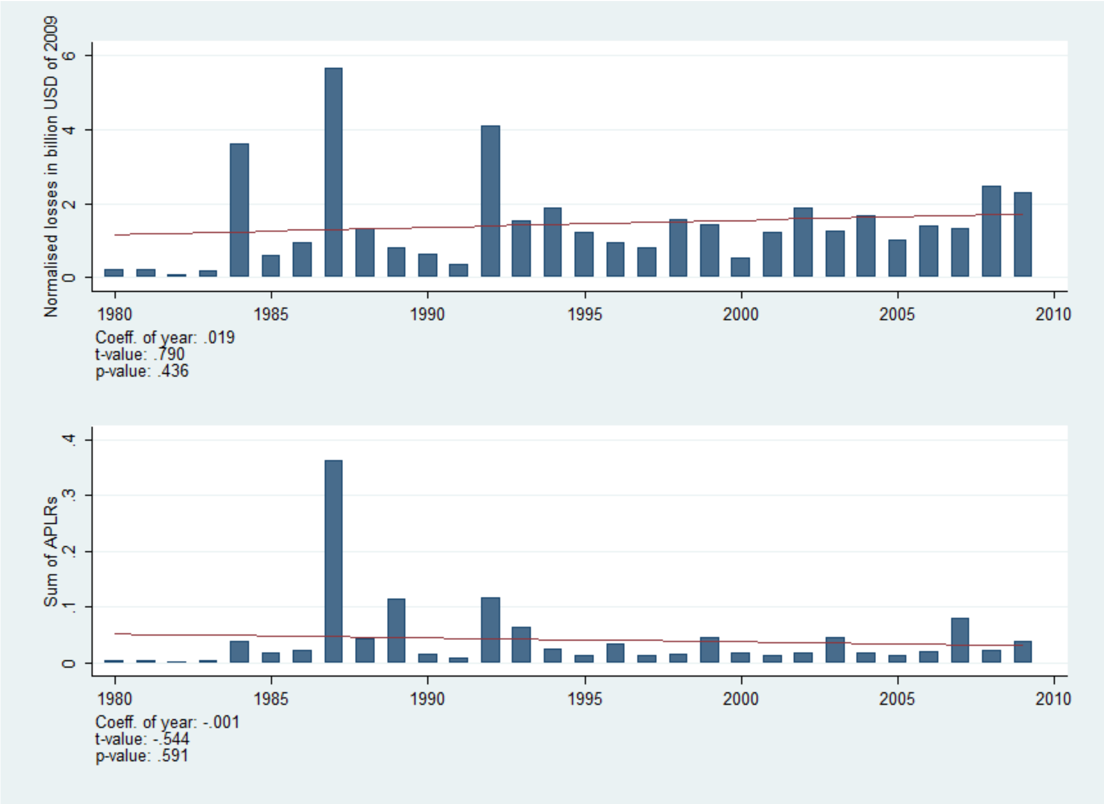
Note: Based on 6,507 disasters; Includes damages from flooding (flash flood and general flood) and mass movement (rock falls, landslides, and avalanches).

Figure 7a: Disaster losses from convective events in the United States normalized with conventional approach (top) and alternative approach (bottom)



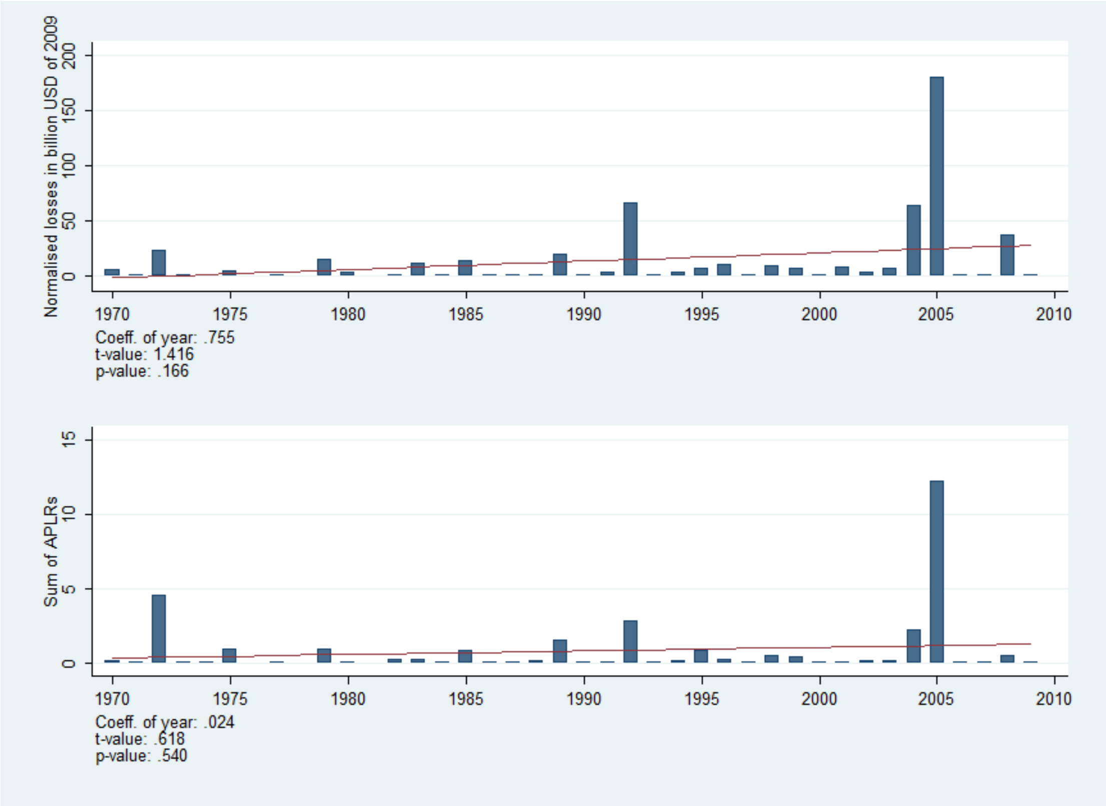
Note: Based on 1,771 disasters; Includes damages from flash floods, hail storms, tempest storms, tornados, and lightning.

Figure 7b: Disaster losses from convective events in Western Europe normalized with conventional approach (top) and alternative approach (bottom)



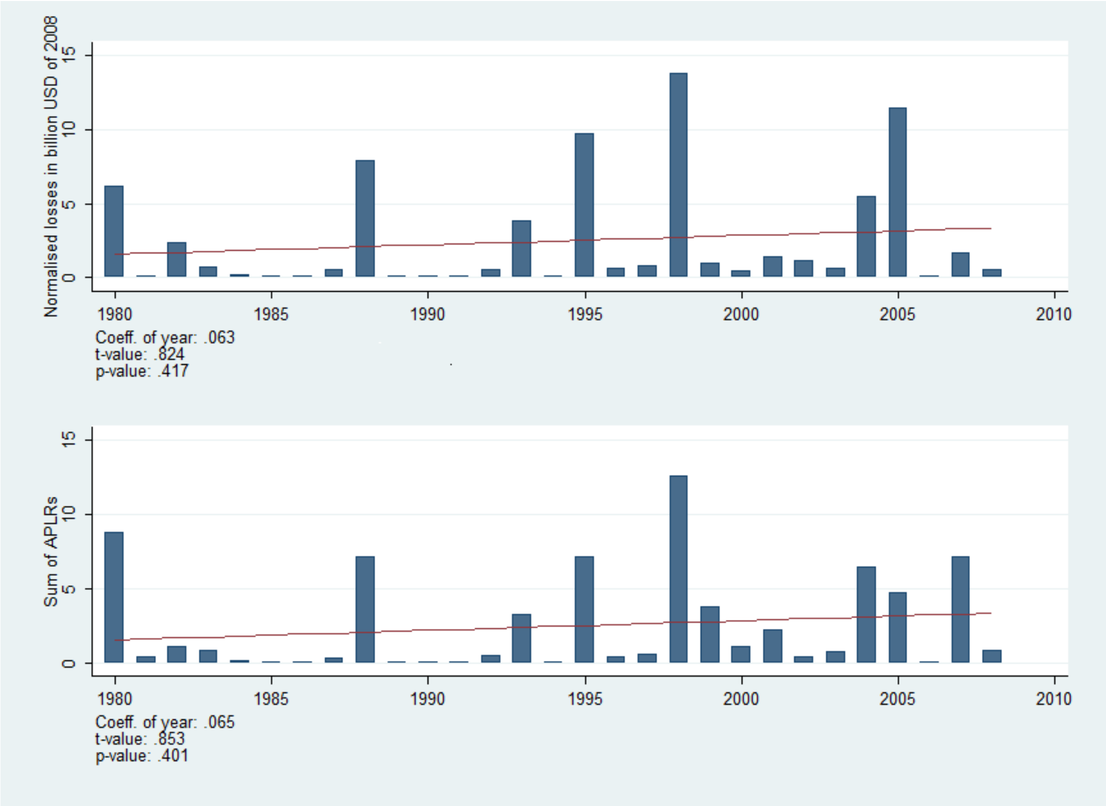
Note: Based on 1,296 disasters; Includes damages from flash floods, hail storms, tempest storms, tornados, and lightning.

Figure 7c: Disaster losses from hurricanes in the United States normalized with conventional approach (top) and alternative approach (bottom)



Note: Based on 118 disasters.

Figure 7d: Disaster losses from hurricanes in Central America and The Caribbean normalized with conventional approach (top) and alternative approach (bottom)



Note: Based on 295 disasters.

Figure 8: Annual frequency count of geophysical and weather-related disasters

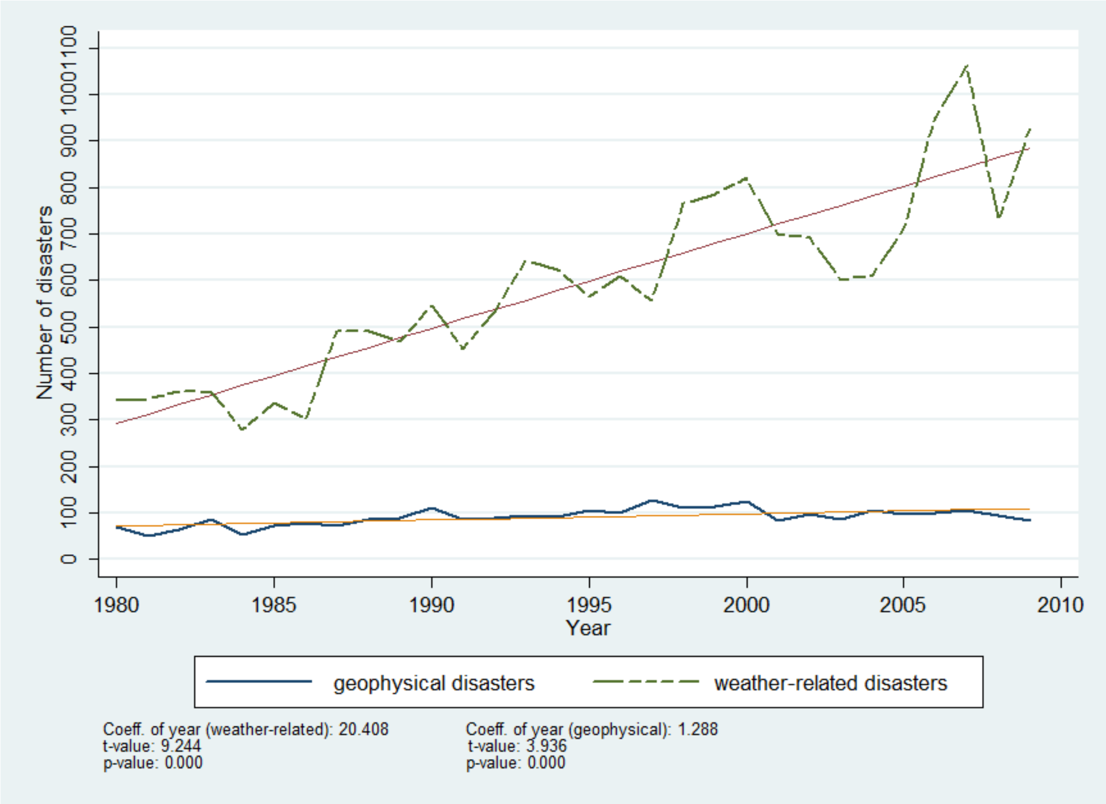


Figure 9: Annual frequency count of major geophysical and weather-related disasters