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Natural Disaster Risk and the Distributional Dynamics of Damages

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Natural Disaster Risk and the Distributional Dynamics of Damages

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Abstract

Literature on climate change and extreme events has found conflicting and often weak results on the evolution of economic damages related to natural disasters, although climate change is likely to bring about an increase in their magnitude (Van Aalst, 2006; IPCC, 2007, 2012). These studies usually focus on trend detection, typically employing mean regression techniques on yearly summed data. Using EM-DAT data, we enrich the analysis of natural disasters' risk by characterizing the behavior of the entire distribution of economic (and human) losses, especially high quantiles. We also envisage a novel normalization procedure to control for exposure (e.g. number and value of assets at risk, inflation), so to ensure spatial and temporal comparability of hazards. Employing moments and quantiles analysis and non-parametric kernel density estimations, we find a rightward shift and a progressive right-tail fattening process of the global distribution of economic damages both on yearly and decade aggregated data. Moreover, a battery of quantile regressions provide evidence supporting a substantial increase in the upper quantiles of the economic damage distribution (upper quantiles of human losses tend to decrease globally over time, mostly due to adaptation to storms and floods, but with a worrying polarization between rich and poor countries). Such estimates might be even conservative, given the nature of biases possibly affecting the dataset. Our results shows that mean regressions underestimate systematically the real contribution of the right tail of the damage distribution in shaping the trend itself.

Keywords: natural disasters; quantile regression; economic damages; climate change.

JEL codes: Q51, Q54, Q56.

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1 Introduction

Climate change is likely to bring an increase in the frequency and intensity of certain types of natural hazards (Van Aalst, 2006; IPCC, 2007, 2012). While there is little doubt that natural hazards have risen in number over time, it remains unclear what the behavior of the associated damages is. The literature on climate change and extreme events has found indeed conflicting and often weak results on the evolution of economic damages related to natural disasters. In this paper we provide a novel perspective on analysis of natural disasters focusing on tail risk, characterizing the behavior of the entire distribution of economic damages, especially considering high quantiles.

Natural disasters can be seen as the combination of a geo-physical events and human vulnerabilities it might affect - e.g. population, capital, land usage. Damages are then evaluated as variations in the vulnerabilities that can be attributed to the occurrence of the disaster. To study the behaviour of damages across time and space, we employ data from the EMDAT database (Guha-Sapir et al., 2015). In particular, we consider those disasters (in 189 countries from 1960 to 2015) that can possibly be associated with climate change: floods, extreme temperatures, droughts, storms, wildfires and landslides. We also provide a detailed discussion of possible shortcomings and biases present in the data. Then, we couple disaster data with macroeconomic and demographic data by merging EMDAT with information from the PWT (Feenstra et al., 2015) and we geolocalize all the events, so to recover cell-based climate data trough spatial-matching.

We do not employ standard normalization techniques, but we envisage a convenient generalization of the APL approach proposed by Neumayer and Barthel (2011) which do not impose *a priori* restrictions on the interaction between time trend and any measure of wealth. Our procedure leads to the estimation of a "pure" time trend, instead of interaction term, which is typically obtained if data are normalized before estimating the chosen model.

We then go beyond standard statistical approaches based on mean regressions and yearly sum of damages, focusing on the behavior of the whole damage distribution, considering each single disaster event. Indeed, as pointed out by Huggel et al. (2013), "although trends can be evaluated statistically for moderately extreme events, an important contribution to climate-related damage arises from very rare weather events for which — by virtue of their rarity — it is difficult to gain sufficient statistical power to detect any trends". Accordingly, we argue that retaining the analysis at the disaster level not only reduces the impact of underreporting bias, which can seriously affect the analysis, but it also allows us to investigate the behavior of the right tails of the distribution, whose evolution over time might be crucial in explaining the evolution of natural disasters related to climate change.

Employing moments and quantiles analysis and non-parametric kernel density estimations, we find a rightward shift and a progressive right-tail fattening process of the global distribution of economic damages both on yearly and decade aggregated data. On the contrary, when casualties are considered, we observe a leftward shift of the distribution and a progressive concentration of mass density around zero. These findings are robust to various types of normalizations.

We further analyze trend evolution more formally by means of quantile regressions using various types of controls, including dummy specifications for income class, disaster type and Köppen-Geiger Climatic Classification - derived from spatial matching with Kottek et al. (2006) - and relative interaction terms. Upper quantiles of human losses distributions are found to decrease globally over time. Such a behavior is mostly explained by advancing adaptation towards storms and floods, while extreme temperatures are killing and affecting more people nowadays. However, a worrying polarization effect between rich and poor countries (and along several climatic zone) is documented. For what concern economic damages, we provide evidence of a substantial increase in the upper quantiles of the damage distribution (from 75th on) at a pace which is increasing along quantiles. Rise in economic damages appear to be particularly dramatic in case of big storms and floods (as well as, on the spatial dimension, in tropical and temperate countries). As a robustness check, we experiment with several different model setups, controlling for population dynamics, wealth effects, relative interaction terms and varying the estimation time window (starting from 1960, 1970 and 1980): our results indicates that trend estimation remains broadly unaltered.

Our results show that mean regressions systematically underestimate the real contribution of the right tail of the distribution in shaping the trend itself, leading often to non-significant estimates. Given the nature of the biases possibly affecting the dataset, we believe that our results might be even conservative. In this view, we claim that our results help in explaining barely significant estimates on trend detection, as mean behavior palely reflects meaningful changes in the right tail.

The rest of the paper is organized as follows: in Section 2, we provide a critical review of the literature. In Section 3 we provide a detailed exposition of the methods we use, while Section 4 contains an overview of the principal features of EM-DAT dataset. Section 5 contains descriptive evidence about the main variables, results from quantile regressions and from non-parametric density estimations. Finally, Section 6 concludes.

2 Literature review

Natural disaster risk can be defined as the product of three factors: (1) the probability of the hazard; (2) the exposure, i.e. the population and/or assets potentially affected by hazards; (3) the sensitivity, i.e. the human and economic losses if population and assets are affected by a hazard. In particular, such a product gives the direct risk, which does not account for resilience, i.e. the capacity to react and recover from the occurrence of an hazard. To make an example, the economic risk from a 100-year flood is equal to the product of the probability of such an event (i.e., 1% per year), the economic value of the assets located in the 100-year flood plain exposed to the hazard, and the ratio of losses to exposure value in case of a 100-year flood. In that case, the economic risk from the 100-year flood is equal to the average annual economic losses from 100-year floods (Hallegatte, 2014).[1] Understanding the dynamics of natural disaster damages is then fundamental to gauge insights on present and prospective risks from extreme natural events.

A large body of empirical literature has discussed about the presence of increasing trends in damages once data have been duly normalized.[2] Trend detection is important for at least two reasons. *First*, its presence for absolute damages coupled with absence for normalized ones, would suggest than the main drivers for increasing losses lie in socio-economic factors (e.g. increases in exposed assets values). On the contrary, in case a positive trend would be found in both cases, a legitimate question would concern whether these behaviors can be attributed to climatic factors (see Bouwer, 2011 and the special issue introduced in Helmer and Hilhorst, 2006). In other words, a significant trend in normalized losses - i.e. when properly controlling for the wealth at risk in case of event - might be a relevant trace of on-going climate change. *Second*, the presence of an upward pattern in disaster losses would imply larger risks to be borne in the future and calling for more attention in natural disaster risk management (Thomalla et al., 2006; Schipper and Pelling, 2006; Hallegatte, 2014).

A crucial issue in the investigation of trends concerns the normalization of losses to make them comparable across time and space (a detailed discussion on normalization procedures usually adopted in the literature is provided in Appendix B). Conventional normalizations typically adjust for inflation, population and wealth per capita (Pielke and Landsea, 1998). However, although they controls for the rate of change of normalizing factors, they fail to account for their absolute size, thus making contemporaneous comparison of events taking place in different areas flawed (Neumayer and Barthel, 2011). With such normalizations, most studies come to the conclusion that there is no evidence for a

[1] Clearly, such an example assume that probability can be proxied by the historical frequency of the event.

[2] More precisely, one stream of research pertains to the climate science literature and focuses on climate/weather data (see e.g. Visser and Petersen, 2012), while the other is concerned with losses associated with extreme impact events (see e,g, Bouwer et al., 2007; Bouwer, 2011). The present paper aims at contributing to the latter flow of studies.

rising long-term trend in normalized weather damages (Pielke and Landsea, 1998; Pielke et al., 2008; Schmidt et al., 2009). On the other side, some papers find evidence in favor of a positive long-run trend (Schmidt et al., 2009; Gall et al., 2011), at least for selected hazards. Both the IPCC and the Stern review point to the existence of increasing losses from extreme natural events (IPCC, 2001; Stern, 2007) and, for this reason, have been criticized in Pielke (2007).

Moving away from the conventional normalization approach, Neumayer and Barthel (2011) propose an Actual-to-Potential-Loss (APL) one, where normalization is achieved through the ratio between the actual loss experienced and the total wealth available in that area (maximum loss conceivable). The show that, at the global level, no statistically significant trend can be claimed for pooled normalized losses. However, as soon as one starts disentangling the data, some patterns emerge: for example a strong (negative) trend is found for developed countries, while none is reported in any areas other than the US and Canada. Interestingly, the majority of statistically non-zero trends found in Neumayer and Barthel (2011) (either focusing on geographical area or hazard type) are negative, possibly indicating evidences of successful adaptation or mitigation policies.[3] Upward and significant dynamics are found, instead, using insured loss data for the US and Germany, while at global level no trend has been detected (Barthel and Neumayer, 2012). Consistently, Visser et al. (2014) report stabilized, constant loss patterns at global scale, but highlight heterogeneity across damage indicators (economic losses, deaths and people affected) and geographical areas.

Overall it seems that, *independently form the normalization adopted*, the literature finds no statistically significant upward trend in global natural disaster losses. A relevant feature that ties together the vast majority of the studies presented above concerns the treatment of the data. In particular, they all focus on yearly-aggregated data, i.e. the sum of all the damages occurring in a given year over a specified geographical area, eventually conditioned on hazard type. Moreover, the statistical analysis usually employ OLS regressions (e.g. Barredo, 2009; Neumayer and Barthel, 2011; see instead Visser et al., 2014 for the application of integrated random walk models). Despite the advantages given by such clear-cut procedures, aggregating disaster data might reduce our understanding of the evolution of risk. For instance, as disaster risk is usually quantified through average annual disaster losses (Hallegatte, 2014), one should compute the average of the damages instead of the sum of losses over a year to approximate risk. However, one could resort to more sophisticated measures of risk commonly employed in finance, decision theory and reliability engineering (see e.g. Paté-Cornell, 1996; Artzner et al., 1999; Szegö, 2002). The majority of such measures require to extract additional information

[3]Neumayer and Barthel (2011) are well aware of the possible shortcomings from their estimation due to absence of controls for adaptation and to data quality, and repeatedly warn the reader about the interpretation of their findings.

from the distribution of hazardous events beyond the average (see e.g. the Value at Risk, cf. Linsmeier and Pearson, 2000, for more information). In this paper, we try to account for such issues employing a novel normalization procedure and by characterizing natural disasters' risk considering the behaviour of the whole distribution, in particular that of high quantiles, i.e. the right tail. In the next Section we will spell out the details of our procedure.

3 Methodology

Our analysis focus first on repeated non-parametric distributional estimates of disaster-induced losses over time. More specifically, we rely on Gaussian kernels with automatic bandwidth selection using the Silverman's approach (Silverman, 1986).

We then run a battery of quantile regressions to investigates the presence of trends in different areas of the distribution.[4] Indeed, while the use of kernel density estimates allows a visual inspection of the movements in the distribution of deaths, people affected and monetary damages, quantile regressions provide a quantification of such dynamic patterns and straightforwardly allow for statistical testing.

Such methodological choices are motivated by two reasons. On the one side, the inconclusiveness of results of literature employing regressions on the mean (Pielke and Landsea, 1998; Neumayer and Barthel, 2011). On the other side, the blossoming evidence that natural disasters induce fat-tailed distributions of the damages (Becerra et al., 2012; Mendelsohn et al., 2012) suggests that percentiles can be a simple yet robust statistics summarizing extreme, low-probable events. Additionally, the presence of heavy tails has been proved to dramatically change policy implications in a variety of climate economics models (Pindyck, 2011; Weitzman, 2011), pointing to the relevance of correctly identifying the shape natural disasters' losses. Quantile regressions have been successfully employed to investigate trends in cyclone strength (Elsner et al., 2008; Kossin et al., 2013), also accounting for both spatial and temporal distributional changes (Reich, 2012). However, to our knowledge, it is applied for the first time to the analysis of socio-economic impacts from natural disasters in order to account for the possible impact of climate change.

We estimate the impact of disaster on number of people killed (Deaths), number of people affected

[4] From a technical perspective, we use the modified version of Barrodale-Roberts algorithm as proposed in Koenker and d'Orey (1987) for quantile regressions. All estimation exercises are performed using the *quantreg* and *tidyverse* R-packages.

(Affected) and economic damages (Damage) employing the baseline empirical models:

$$\text{Deaths}_{it} = \alpha_1 + \beta_1 \text{Trend}_t + \gamma_1 \text{POP}_{it} + \phi \mathbf{x}'_{it} \tag{1}$$

$$\text{Affected}_{it} = \alpha_2 + \beta_2 \text{Trend}_t + \gamma_2 \text{POP}_{it} + \varphi \mathbf{x}''_{it} \tag{2}$$

$$\text{Damage}_{it} = \alpha_3 + \beta_3 \text{Trend}_t + \gamma_3 \text{GDP}_{it} + \theta \mathbf{x}'''_{it} \tag{3}$$

where Trend_t is a standard trend variable, GDP_{it} is a measure of the size of the economy (country-level) where a disaster i happens at time t, POP_{it} is the total population size of the country affected by the disaster, and $\mathbf{x}''_{it}$, $\mathbf{x}'_{it}$ and $\mathbf{x}'''_{it}$ are sets of additional control variables that we include in the various specifications we test. Such linear models are convenient for two reasons. First, they offer a simple interpretation of the parameters to be estimated and allow a variety of estimation methodologies. Second, they overcome the loss normalization debate (see Appendix B for further details) and leave the researcher free to choose what variables to control for in her/his analysis (e.g. the potential effect of population dynamics on total destroyable wealth as in Noy, 2009; Kellenberg and Mobarak, 2008). Note that our specifications provide a generalization of the actual-to-potential loss (APL) approach adopted by Neumayer and Barthel (2011). A more fine grained comparison is provided in Appendix B.

4 Data

Our analysis relies on the *Emergency Events Database* (EM-DAT) set up by the *Center for Research on the Epidemiology of Disasters* (Guha-Sapir and Below, 2014) - hereafter CRED - containing data on natural hazards since the beginning of 20th century.[5] CRED definition of a natural disaster is "a situation or event which overwhelms local capacity, necessitating a request to a national or international level for external assistance; an unforeseen and often sudden event that causes great damage, destruction and human suffering". However, entry requirements for an event to be included in the dataset are quite blurred, and there is no cut-off measure. Among all recorded disasters, we consider only events which took place after 1960 and we deal with only six different types of disasters that can directly related to climate change: floods, extreme temperatures, droughts, storms, wildfires and landslides. The ensuing total sample size includes 10901 events.

For each record, the EM-DAT reports basic information on the disaster occurrence, such as the start and end date, country, location (when available), type of disaster plus three types of loss data:

[5] Additional information as well as the form to request access to the data are provided here: `http://www.emdat.be`. For other natural disaster databases, see Desinventar, SwissRe Sigma and MunichRe NatCat.

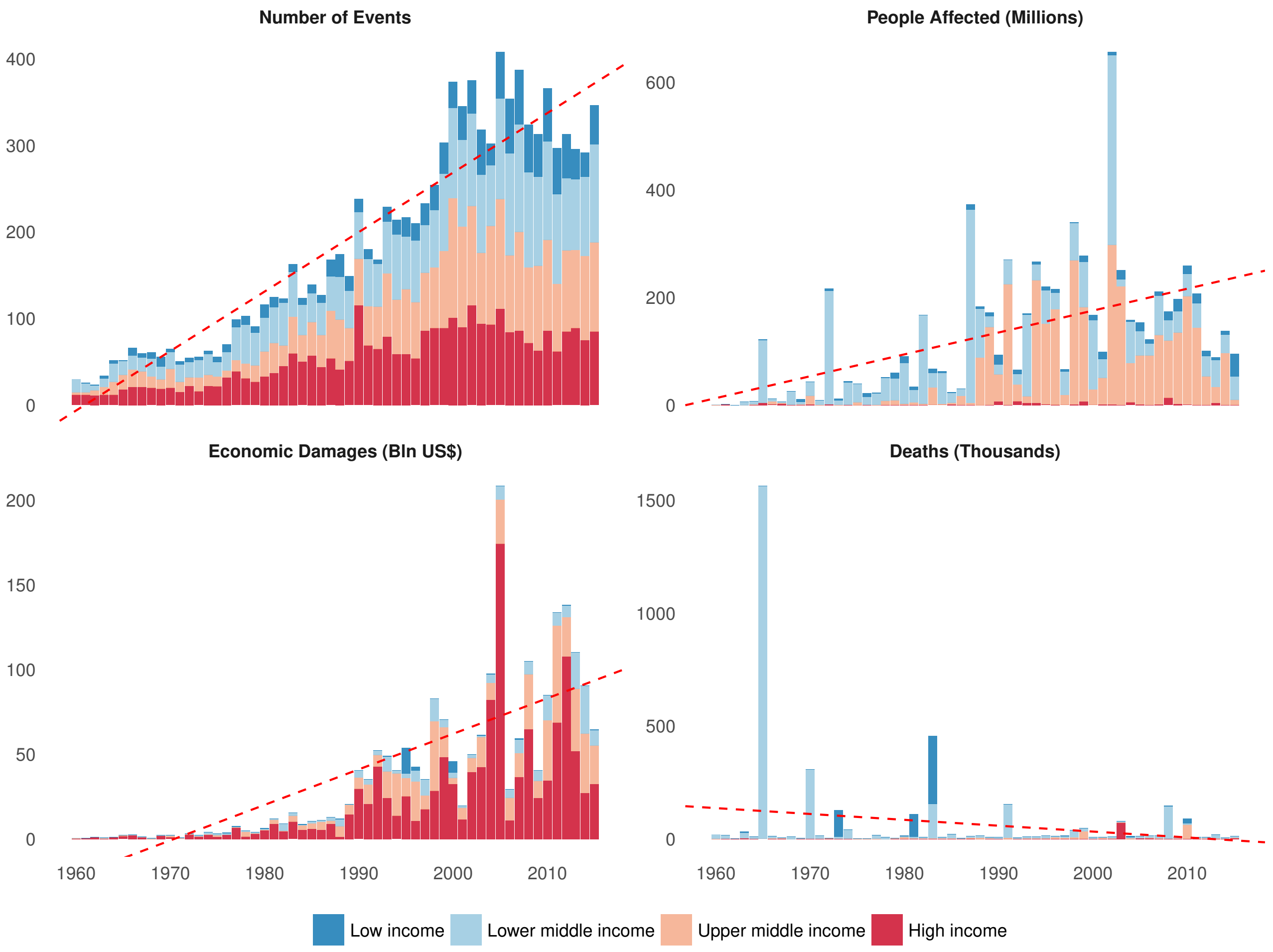

Figure 1: Number of recorded disasters and yearly sum of the three types of losses, by income level. Red dashed lines are OLS trend estimates. Time span: 1960-2015.

number of people killed, number of people affected and economic damages.[6] As disasters data suffer from several shortcomings, one must understand what is exactly measured by each variable, bearing in mind that these are often broad estimates about complex and composite phenomena, not point measurements.

While deaths are unambiguously recorded, the concept of people affected is fuzzier, being the sum of people that, after a catastrophic event, are left homeless, injured or that require immediate assistance in the aftermath of the emergency. Comparisons across time and space must then be handed carefully. Economic damages are defined by CRED as the "value of all damages and economic losses directly or indirectly related to the disaster". Thus, such damages include infrastructural monetary losses, as well as direct and indirect harm to production (e.g. interruption of production process because of damaged plants), social (e.g. loss of jobs) and environmental economic costs.

[6] EM-DAT data is collected, when possible, through official institutions (national governments, international organizations such as UN or EU), intergovernmental institutions (World Bank) and reinsurance companies (SwissRe, MunichRe). When official sources are unavailable, they are integrated through press records (AFP). Around two third of records are based on official governmental, statistical or financial sources (Kron et al., 2012).

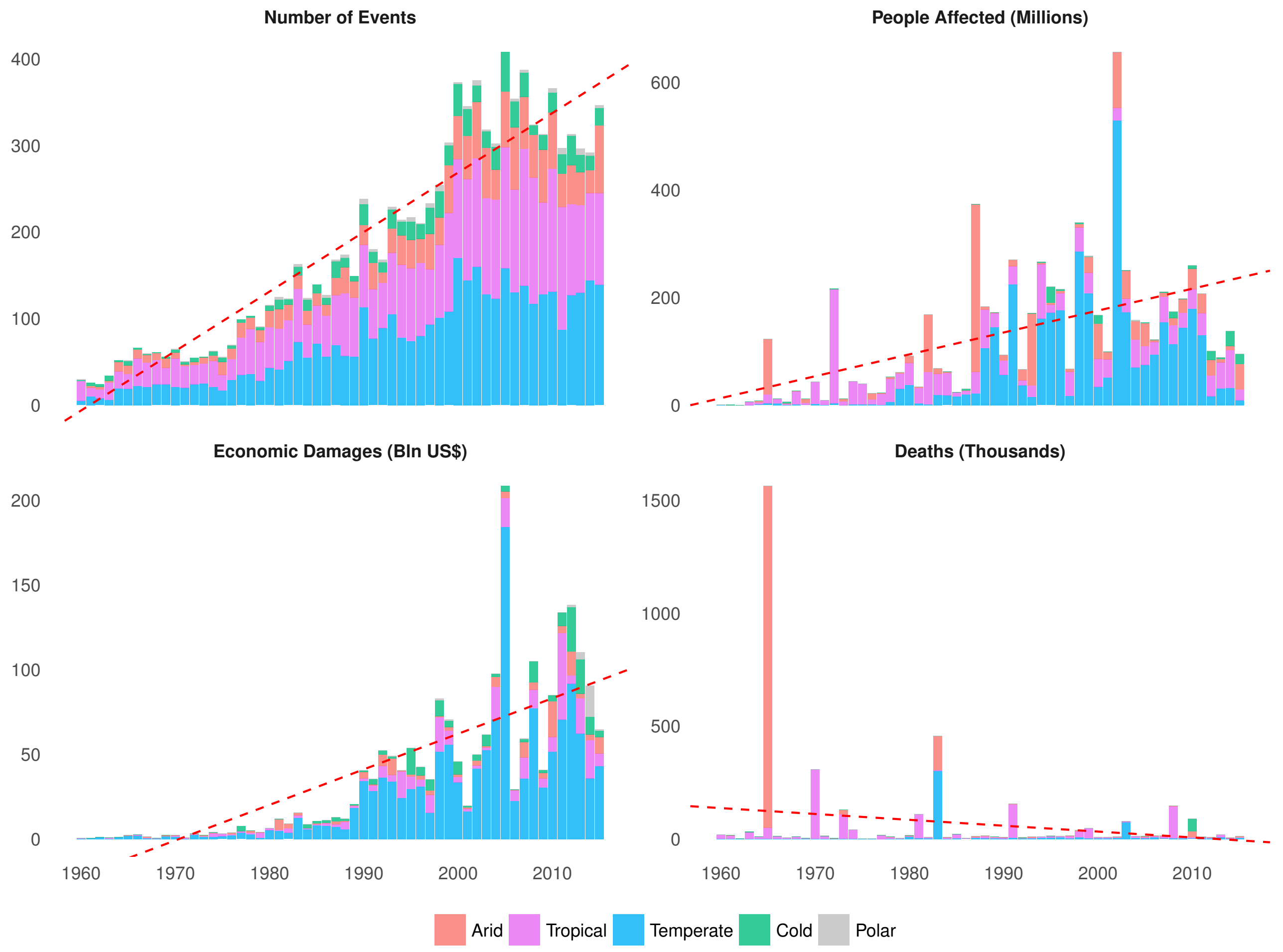

Figure 2: Number of recorded disasters and yearly sum of the three types of losses, by Köppen-Geiger climate zone. Red dashed lines are OLS trend estimates. Time span: 1960-2015.

Figure 1 shows the evolution of the number of recorded disasters and of the three type of losses over 1960-2015, grouped by income level (see Appendix A for details). The number of observed disasters steadily increases over time, which can partly explain the rising number of people affected and recorded economic damages. While the proportions between income classes in recorded events are relatively stable over time, people affected are largely recorded in poor countries, although with a notable recent increase in upper-middle income countries. As reported in Appendix D (Figure D.4), the vast majority of people affected are from Asian countries, followed by Africa [7]. The only damage measure that tends to decrease is the count of deaths, largely driven by the disappearance of huge outliers. Dead people are almost entirely recorded in poor countries (mostly Asia and Africa). Interestingly, deaths appear to have an increasing trend in upper-middle and high income countries (Appendix D, Figure D). On the other hand, economic damages (which have been increasing mostly everywhere and globally at a seemingly exponential pace) appear to be eminently a rich country issue. Such evidence highlights the

[7] We defer to Appendix D for more detailed charts on the evolution of all type of losses, grouped not only on the income level and Köppen-Geiger climate zone dimensions, but also on the continent and hazard type dimensions.

Table 1: Summary statistics by decade. Standard deviations are reported within parenthesis.

	1960s	1970s	1980s	1990s	2000s	2010s
Deaths	3651 (69881)	756 (11955)	474 (9331)	146 (3209)	93 (2409)	79 (1378)
People Affected (Thousands)	423 (4792)	739 (7970)	857 (9390)	884 (9127)	626 (7007)	466 (3920)
Economic Damages (Mln $)	29.4 (150)	52.1 (242)	84.7 (380)	224 (1236)	205 (2357)	326 (1873)

need to control for total wealth when making across-time and space comparisons in economic damages.

To improve the spatial resolution of any possible control variable, we geolocated the entire EM-DAT dataset (i.e. we retrieved latitude and longitude for each event) through Google Maps API, using the location information originally present in the dataset (details in Appendix A). This allows us to retrieve, trough spatial matching, the climate zones in which each event took place according to the Köppen-Geiger classification (i.e., arid, tropical, temperate, cold and polar zones). Figure 2 clearly shows that most of the extreme events took place in tropical and temperate zones, with the latter experiencing most of the economic damages, not only because of their higher wealth, but also because temperate zones typically cover much more land area than tropical ones.[8] Similarly, most of the people affected are recorded in these two zones, and the increment in affected people is generalized, but much stronger (especially in recent times) in temperate areas. Deaths tend to decrease in tropical and arid zones, while they have been increasing in temperate and cold zones.

Disaster data are well know for being subject to several issues, the most serious one probably being under-reporting in economic damages (Guha-Sapir et al., 2013). As a consequence, the steady increase in the number of events shown in Figures 1 and 2 might be due to past under-reporting, as the bias gets more severe the further back in time one goes (Kron et al., 2012). As we are interested in trend detection, focusing the statistical analysis on damages distributions, rather than sheer sums, can significantly reduce the bias induced by under-reporting, assuming that such bias is evenly distributed across disasters of different magnitudes in each year. Such assumption is however unlikely to be satisfied: one can reasonably presume that, in any given year, it is more likely that an event of small

[8] Although country income class and climatic zone are certainly related, they are far from being the same thing. We performed a multivariate Pearson Chi-squared Test on the data, which reject the null hypothesis of independence. The Cramèr's V, which ranges from 0 (independent categorical variables) to 1 (identical categorical variables), is indeed equal to 0.35.

proportion fail to enter in the database compared to a major one. On the chronological dimension, one can presumably assume that such bias has been reducing over time. Year after year, more disasters enter the database as institutions get better at collecting data, and the proportion of unrecorded small events gets smaller and smaller. By the same token, that applies also to events with zero recorded economic damage [9]. In other words, as time goes by a big and growing percentage of recorded disaster is represented by small or zero damage events simply because underreporting bias is reducing [10]. We discuss the implications of such bias on our results in Section 5.2.

The importance of keeping the analysis at the disaster level is evident in Table 1, where decade-aggregated mean for people affected is increasing up to the 80's but decreasing since then. When summing data on a yearly basis (*de facto* removing zeros) - as in Figures 1 and 2 - the trend was undoubtedly positive. This might indicate that increases in total affected per year is at least partially due to an increasing number of events (hence possibly boosted by past underreporting). In a nutshell, summing losses on a yearly basis not only exacerbates past underreporting, but also induces a mistreatment of zeros.

5 Results

Retaining the analysis at the disaster level allow us not only to better control for possible biases, but also to investigate various parts of the loss distributions. In what follows, we first present the yearly evolution of the moments of the distribution (Section 5.1), as well as of selected quantiles. We then display and discuss repeated kernel density estimation of decade-level loss distributions. Our hypothesis are then tested through dedicated quantile regressions of models (1), (2) and (3) (Section 5.2). Finally, in Section 5.3 we focus on possible patterns in human losses by way of 2D kernel density estimation. Further robustness checks are reported in Appendix C.

5.1 Descriptive evidence

Let us start studying the yearly evolution of the moments of the damage' distributions in order to detect possible directions of losses over time. Natural variability clearly plays a role in shifting and shaping distributions from one year to another, although one can reasonably assume that over a 56 years time span such effects are washed out.

[9]Some economic damages are recorded as zeros because of a lack of a reasonable estimate. As documented in Guha-Sapir et al. (2013), the percentage of zeros sharply decrease with the severity of the disaster (according to the EM-DAT classification), and such decrease get sharper as data gets more recent.

[10]Also, inaccurate estimates coming from less reliable sources (such as press) are more likely to concern small scale disaster, as the lower the magnitude the higher the incentive for official institutions to produce scrupulous statistics.

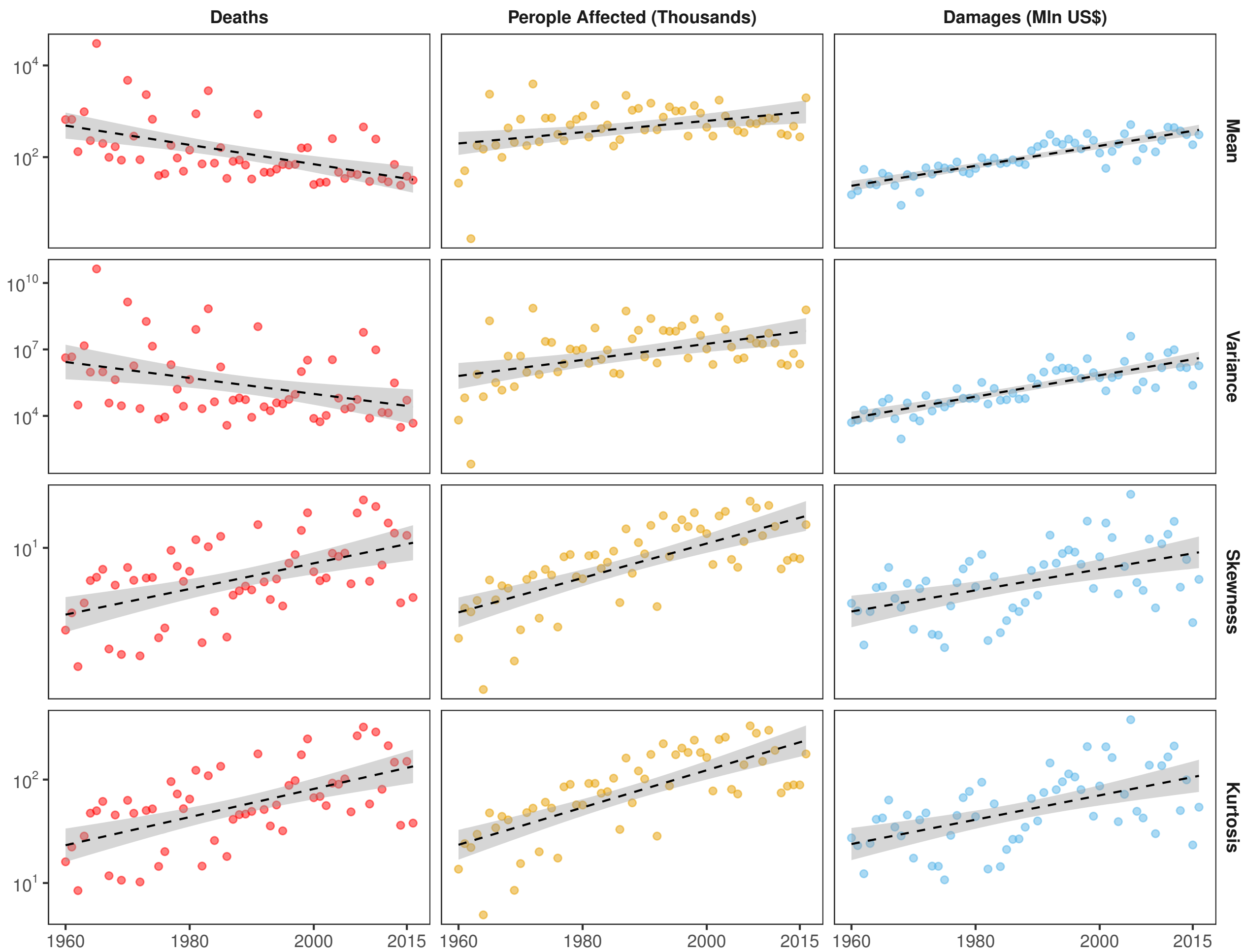

Figure 3: Summary of yearly disaster distributions based on moments, by type of loss. Vertical log-axis. Dashed lines are linear OLS best fitting lines. Time span 1960-2015.

Figure 3 shows the evolution of mean, variance, skewness and kurtosis of the three loss measures at the global level. Deaths exhibit a downward trend in mean and variance, but increasing skewness. Since cubing deviations gives the big ones even greater weight, increasing skewness means few points are getting further to the right of the mean, and lots of points getting closer to the left of the mean. As mean is decreasing, we interpret this as evidence of damages getting more concentrated towards small values. Same goes for kurtosis, which is increasing as well: a larger proportion of the (decreasing) variance is explained by extreme values on either sides of the distribution, most likely a fattening left tail in this case.

When one considers economic damages, all four moments are increasing over time, pointing to a progressive shift to the right of the whole distribution, with a contemporaneous fattening process of the right tail. Affected people display a similar behavior, although the increase in the year mean and variance is almost zero.

Evidence from selected quantiles of yearly distributions, shown in Figure 4, confirms such a reading

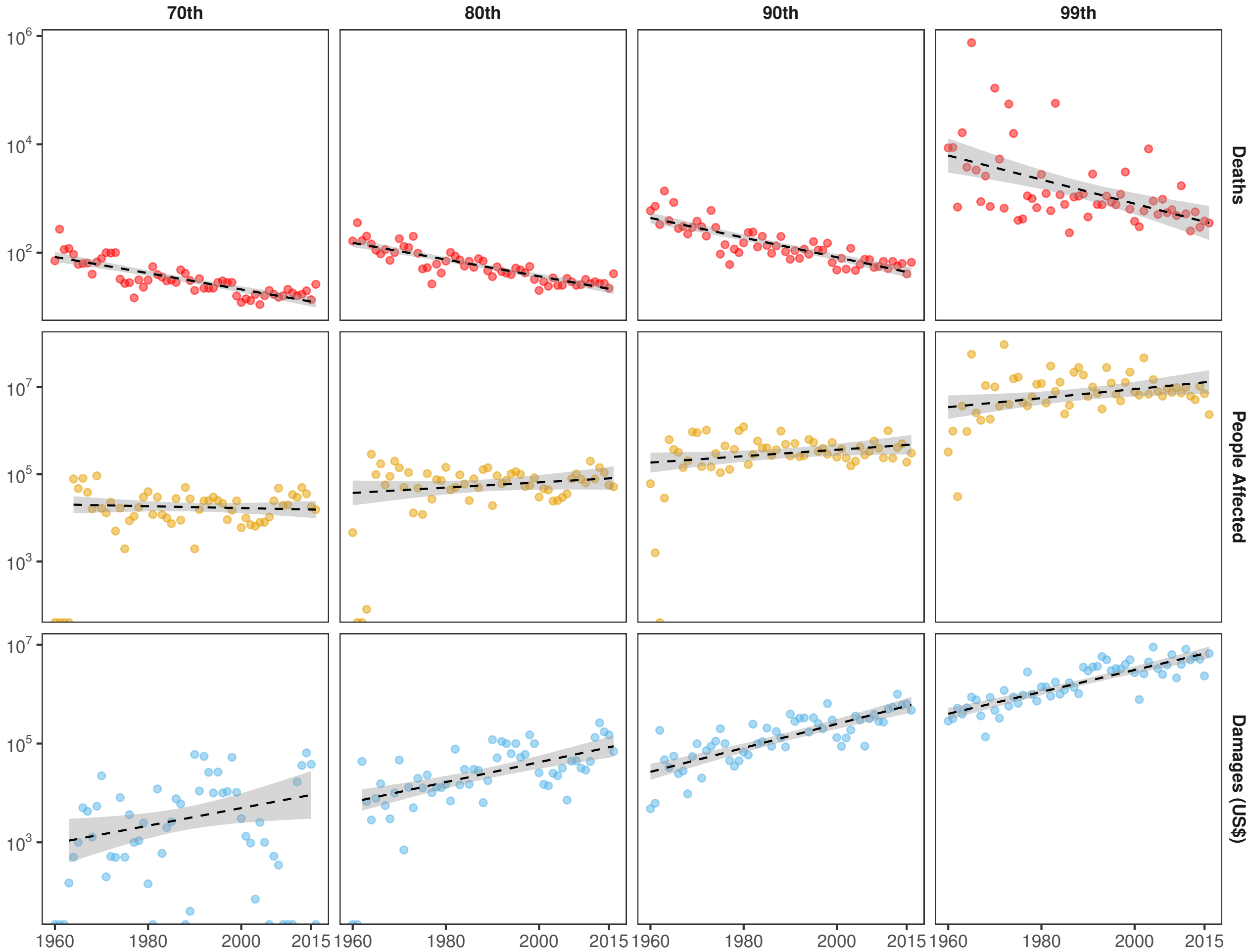

Figure 4: Selected quantiles of yearly disaster distributions, by type of loss. Vertical log-axis. Dashed lines are linear OLS best fitting lines. Time span 1960-2015.

of the data. High quantiles (70th, 80th, 90th and 99th) tend to decrease over time for deaths, while they show an increasing pattern for economic damages. Both trends clearly get steeper across quantiles in both cases, a particularly remarkable behavior since y-axis is in logs. Finally, affected people do not show any particularly pronounced trend.

We then estimated with non-parametric kernel procedures the evolution of loss distributions in different decades. Grouping observation by decade washes away between-years meteorological variability.[11] Results are in line with those just presented and are reported in Figure 5. Distribution of deaths is moving leftwards and so does the median value. Since values are displayed on a log-scale, given the heavily right-tailed nature of the distributions, these movements are actually quite remarkable. Economic damages show instead a rightward shift - even stronger in magnitude - and a progressive fattening of the right tail which can be spotted even on a log-scale. Affected people distribution tends to move in both directions, indicating a relative stability over time.

[11] In order to ease the visualization of the distributions, all disasters with loss equal to 0 have been excluded.

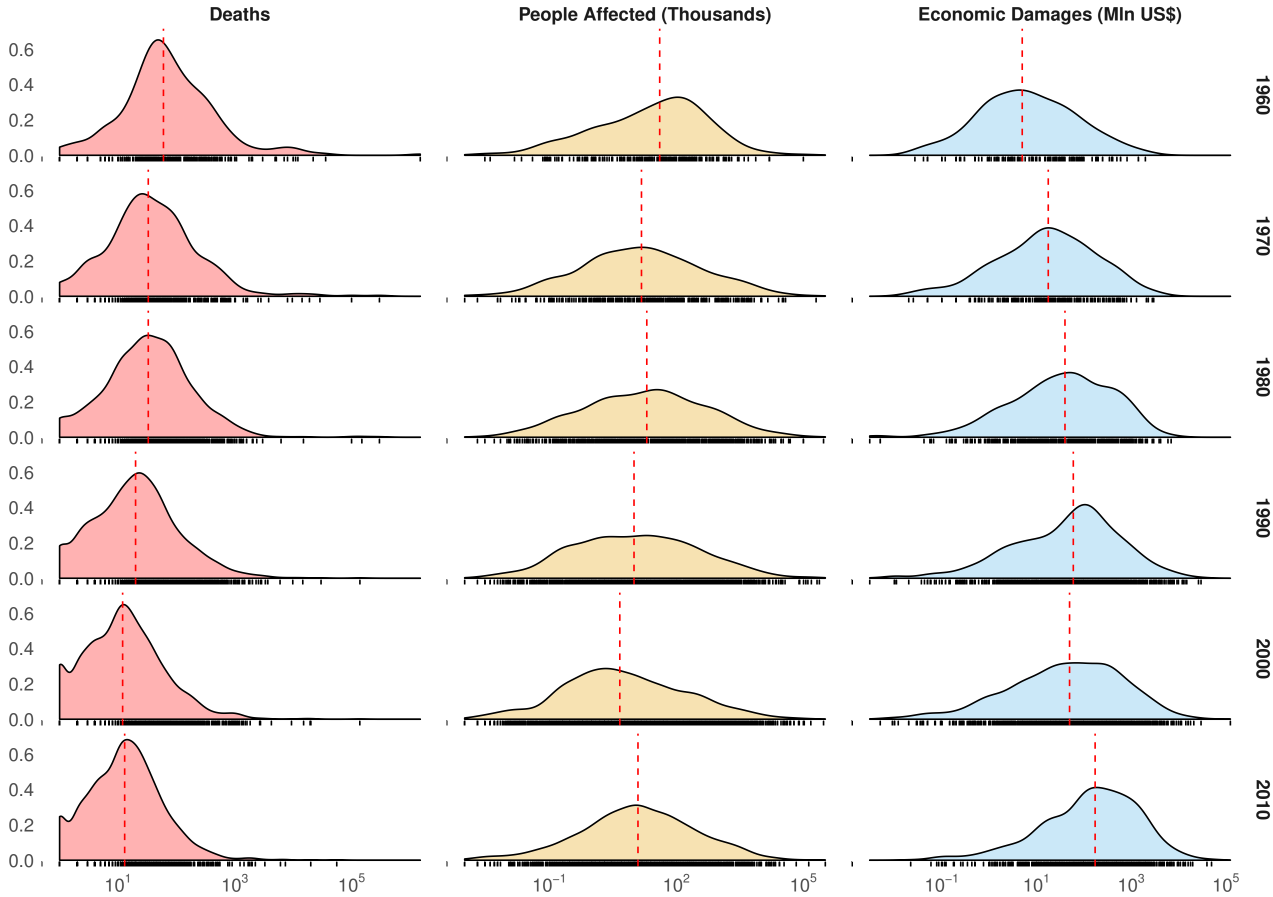

Figure 5: Loss kernel density estimates, by type of loss. Data aggregated on a decade basis. Horizontal log-axis. Dashed red lines represent medians. Zero losses disasters excluded from computations. Kernel is Gaussian. Bandwidth selection is done by Silverman's rule-of-thumb (Silverman, 1986), i.e. 0.9 times the minimum of the standard deviation and the interquartile range divided by 1.34 times the sample size to the negative one-fifth power. Rug plots below each distribution represent marginal distributions. Time span 1960-2014.

Statistics presented so far are based on raw data, i.e. without controlling for exposures. We then check the robustness of our results with respect to different normalization procedures controlling from population and wealth. The evolution of moments, selected quantiles and estimated densities on normalized data remains qualitatively unchanged (see Appendix B). Note that for economic damages, the movement in the median seems to be much less pronounced, while the progressive fattening of the right tail is still well evident.

Given the sheer evolution of the distributions over time, conditional mean regressions could provide weak results on the existence of a trend, as mean - and median - are not robust indicators when most of the changes are due to high quantiles. For this reason, in the next Section we perform a battery of quantile regressions.

5.2 Quantile regressions

As the descriptive evidence suggest that the dynamics of the damage distributions over time is heterogeneous across quantiles, we run a battery of quantile regressions. Our baseline specifications (cf. Eqs. 1, 2 and 3 with $\mathbf{x}'_{it}$, $\mathbf{x}''_{it}$ and $\mathbf{x}'''_{it}$ set to zero) estimate for each single quantile (τ), the associated per-year time trend β_τ. We run several regressions for different values of τ, from 70th to 99th quantile with unit steps. Figures 6 reports the β_τ estimates and those of relative control variables against the corresponding quantile, for all types of loss.

Up to the 70th quantile, $\hat{\beta}_\tau$ are generally very close to zero due to the high number of very low values. This constitutes another piece of evidence supporting the idea that mean cannot be a robust indicator to study disaster dynamics. After the 70th quantile, the estimates for β_τ indicate that upper quantiles tend to decrease over time for deaths and people affected. Moreover, the higher the quantile, the bigger the movement on the left. This finding can certainly be interpreted as an increased adaptation and ability to forecast extreme events (more on that in Section 5.3). Population dynamics turned out to be crucial in explaining affected people (unlike deaths), whose seemingly increasing behavior can thus be explained in terms of higher population (and recorded events).

A diametrically opposed result emerges for economic damages: as shown in the south-east box of Figure 6, upper quantiles tend to increase over time. Such an increase is bigger the higher the quantile, even controlling for wealth proxied by GDP. In our view, these findings provide a plausible explanation for the non-significant results on trend evolution usually found in studies based on mean regressions, which only palely reflect meaningful changes on the right tail of damages distributions. Indeed, as shown in Figure 6, not only OLS β estimate (dashed line) largely underestimate the real impact of major disasters, but it leads to a non-significant β. Results are remarkable also in terms of absolute magnitudes: if one considers, for instance, the 99th percentile, $\hat{\beta}_{99} = 26.385$ (see Table C.1), implying that over a time span of 54 years the damages of the associated disasters have increased by 1424.79 Mln \$, *ceteris paribus*.

Furthermore, potential biases in the data discussed in Section 4 can actually reinforce our results concerning economic damages. Indeed, as both under-reported and zero-damage disasters tend to decrease across both time and disaster magnitude, more and more mass is added to the left part of damages distribution year by year, mechanically shifting quantiles to the left. Despite that, we document a serious rightward movement, whose estimated magnitude can thus even be a conservative

[12] Bootstrap method is explicitly advised in Hao and Naiman (2007), as it makes no assumptions about the distribution of the response. Moreover, "...assumptions for the asymptotic procedure usually do not hold, and even if these assumptions are satisfied, it is complicated to solve for the standard error of the constructed scale and skewness shifts..." (p. 43).

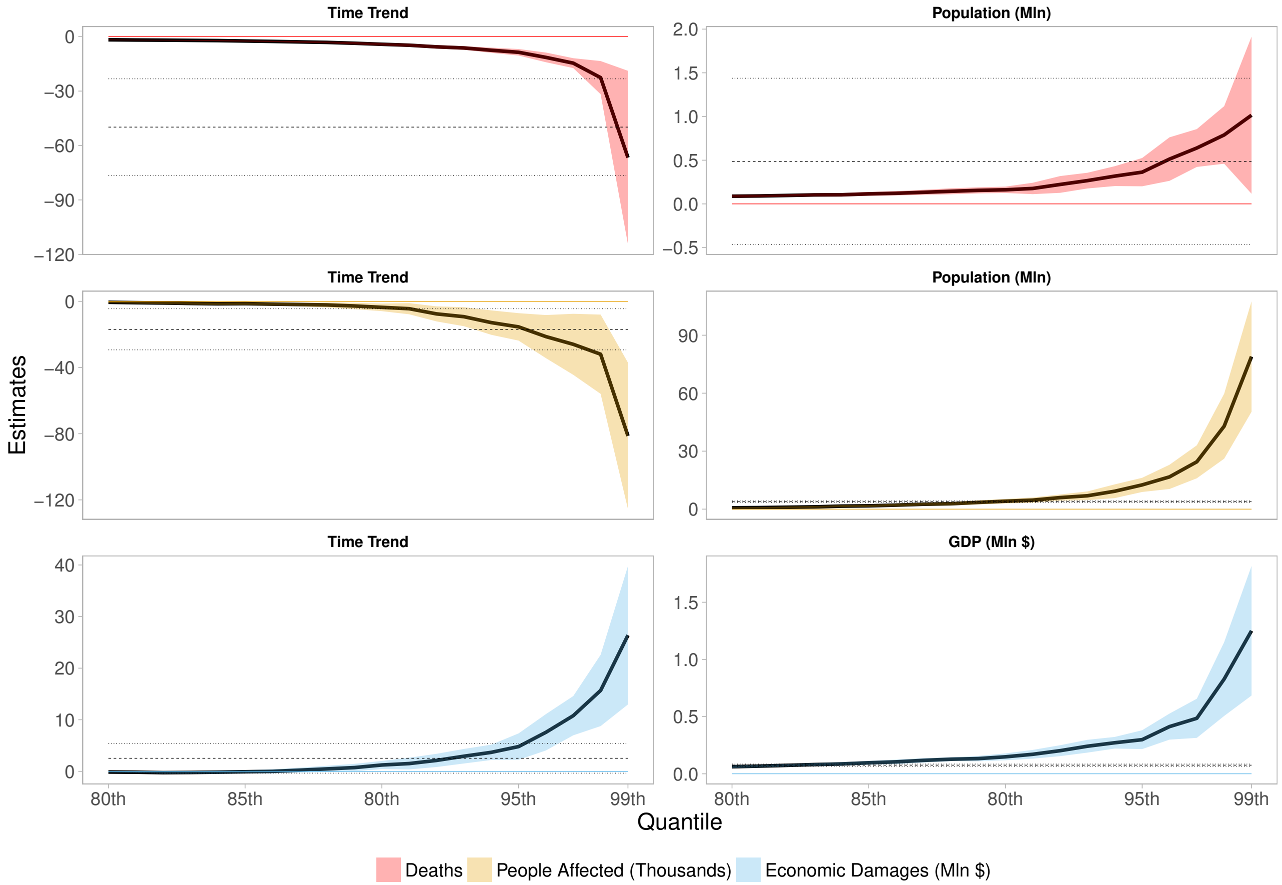

Figure 6: Quantile regressions estimates by type of loss, quantile on x-axis and estimate on y-axis. Baseline model. Method is modified Barrodale-Roberts algorithm (Koenker and d'Orey, 1987)). Colored areas are 95% bootstrapped confidence bands (r=500) [12]. Bootstrap method is x-y pairwise resampling, as recommended in Efron and Tibshirani (1994). Dashed black lines are OLS estimates with relative 95% confidence bands.

one.

In order to test the robustness of our results, we performed the same exercise adding control variables in the vectors $\mathbf{x}'_{it}$, $\mathbf{x}''_{it}$ and $\mathbf{x}'''_{it}$. Results are presented in Appendix C. Adding GDP as a control variable for deaths and people affected do not change qualitatively our results. As far as economic damages are concerned, results do not vary if one enriches the model specification adding population as a control variable and using GDP per capita instead of GDP. We also experiment with varying time-spans, letting our estimation begin in 1960, 1970 and 1980, respectively. Overall results are broadly unaffected in terms of trend estimation, although a smaller number of observation make it more difficult to have small standard errors for such rare events.[13] Notably, a positive and significant trend in upper quantiles is detected even when adopting Neumayer and Barthel (2011) normalization (see model (6) in Table C.1, Appendix C). We also run a baseline regression on economic damages

[13] Appendix B contains also results deriving from OLS estimations on yearly summed data, with varying normalization approaches and time-spans.

adding an interaction term between GDP and the pure time trend (Appendix C, Table C.1, Model (5)): the interaction term is estimated to be very close to 0 and not significant for high percentiles. As already specified in Section 3, such evidence reinforce our model specification which do not impose any non-zero interaction exogenously.

We now focus on economic damages and we reports in Table 2 the estimates obtained adding to the regressions categorical variables for (i) income class, (ii) Köpppen-Geiger climate zones, (iii) disaster type and their interactions with the pure trend variable:

$$\text{Damage}_{it} = \alpha_1 + \beta_1 \text{Trend}_t + \gamma \text{GDP}_{it} + \sum_{i=1}^{k} \delta_i c_i + \sum_{i=1}^{k} \rho_i c_i \cdot \text{Trend}_t, \tag{4}$$

with c_i's being the categorical variables under analysis. Only interaction terms (which can be interpreted as deviation from baseline category trend) are displayed. From the income level perspective, the highest increase in damages is found in the richest countries, although the upsurge is generalized and positive almost everywhere. The only possible exception is represented by low income countries, with an estimated trend close to zero. This may stem from the choice of using GDP - a flow variable - as a proxy for wealth instead of physical capital - a stock variable - that is typically characterized by high measurement errors (Neumayer and Barthel, 2011), as well as from the poor quality of data available for these countries. On the climatic side, trend is found to be positive (and growing across quantiles) in tropical zones and even more remarkably in temperate zones, while no significant increase is found for arid and cold zones. In particular, tropical zones seem to experience a marked increase in damages only for quantiles above 90th, while those below display a negative estimate, possibly reflecting the results of ongoing adaptation efforts carried out in such heavily exposed areas. Note that OLS estimators would have missed to spot significant betas in both tropical and temperate case. On the hazard perspective, the increase in economic damages is particularly relevant in case of storms (and partially floods), which represent the vast majority of the events in our dataset.

Results obtained in this section point to a dramatic increased natural disaster risk, particularly driven by major events: we shall discuss their implications more accurately in Section 6.

Table 2: Quantile regressions estimates for selected quantiles and OLS estimates as in (4) on economic damages, for income class, Köppen-Geiger climate zone and disaster type, respectively. Only interaction terms (ρ_i's') and GDP are displayed. Method is modified Barrodale-Roberts algorithm (Koenker and d'Orey, 1987)). Bootstrapped standard errors according to x-y pairwise resampling algorithm, as recommended in Efron and Tibshirani (1994). p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed.

		70th	80th	90th	95th	99th	OLS
(7) 1960-2014	High (*Base*)	1.028***	3.725***	10.07***	20.791***	70.74***	9.905***
		(0.246)	*(0.525)*	*(1.649)*	*(2.57)*	*(18.286)*	*(2.626)*
	GDP	0.021***	0.051***	0.123***	0.275***	1.047***	0.069***
		(0.003)	*(0.007)*	*(0.017)*	*(0.038)*	*(0.277)*	*(0.005)*
	Low	-1.038***	-3.75***	-10.405***	-22.841***	-75.623***	-10.295*
		(0.245)	*(0.527)*	*(1.634)*	*(2.666)*	*(18.417)*	*(5.41)*
	Lower-Middle	-1.048***	-3.836***	-10.052***	-17.718***	-50.279***	-9.035**
		(0.246)	*(0.524)*	*(1.717)*	*(2.626)*	*(18.196)*	*(3.616)*
	Upper-Middle	-1.063***	-3.901***	-9.25***	-17.732***	-51.915**	-10.218***
		(0.247)	*(0.546)*	*(2.028)*	*(3.781)*	*(24.744)*	*(3.846)*
(8) 1960-2014	Tropical (*Base*)	-0.03***	-0.161***	-0.172	2.435*	17.934***	1.552
		(0.008)	*(0.051)*	*(0.428)*	*(1.336)*	*(4.981)*	*(2.31)*
	GDP	0.023***	0.058***	0.136***	0.266***	1.232***	0.073***
		(0.002)	*(0.008)*	*(0.014)*	*(0.042)*	*(0.222)*	*(0.005)*
	Arid	0.007	0.063	-0.64	-2.562	2.153	-2.466
		(0.012)	*(0.074)*	*(0.691)*	*(3.822)*	*(23.311)*	*(4.572)*
	Temperate	0.038	0.718***	5.168***	11.371***	28.561*	3.091
		(0.026)	*(0.257)*	*(1.067)*	*(3.591)*	*(15.56)*	*(3.258)*
	Cold	0.004	0.864	4.482**	5.984	-15.324	1.893
		(0.099)	*(0.754)*	*(2.151)*	*(4.117)*	*(37.463)*	*(6.311)*
	Polar	0.042	0.149	0.138	-2.298	127.089*	10.983
		(0.059)	*(0.278)*	*(0.645)*	*(27.81)*	*(76.097)*	*(13.711)*
(9) 1960-2014	Storm (*Base*)	0.276***	1.12***	4.97***	10.884***	34.437***	7.092***
		(0.093)	*(0.264)*	*(0.686)*	*(1.446)*	*(10.315)*	*(2.416)*
	GDP	0.022***	0.056***	0.142***	0.285***	1.173***	0.074***
		(0.002)	*(0.007)*	*(0.015)*	*(0.039)*	*(0.252)*	*(0.005)*
	Drought	-0.277***	0.033	2.935	1.075	-58.531	-1.525
		(0.099)	*(0.714)*	*(3.233)*	*(10.123)*	*(59.487)*	*(5.814)*
	Flood	-0.301***	-1.274***	-4.535***	-9.964***	-6.564	-5.982*
		(0.092)	*(0.284)*	*(0.986)*	*(2.445)*	*(15.445)*	*(3.286)*
	Extreme Temp.	-0.222**	-1.059***	-5.364***	-23.073***	-13.598	-8.199
		(0.102)	*(0.287)*	*(2.03)*	*(6.724)*	*(30.955)*	*(7.997)*
	Landslide	-0.334***	-1.167***	-5.033***	-10.959***	-34.626**	-12.584**
		(0.096)	*(0.262)*	*(0.686)*	*(1.442)*	*(15.125)*	*(6.302)*
	Wildfire	-0.267***	-1.064***	-1.907	-3.856	-64.041	-12.981
		(0.095)	*(0.321)*	*(1954)*	*(7.071)*	*(86.061)*	*(8.621)*

5.3 Shedding light on human losses dynamics

While we find strong evidence of increasing damages caused by major natural disasters both on a global scale and across income classes and climatic zones, results concerning deaths and affected people appear to be clear only at the global level. More precisely, results stemming from the estimation of model envisaged in (4) applied to human losses are overall scarcely significant, especially for high quantiles (cf. Appendix C, Tables C.3 and C.2). This could be due to a lack of statistical power needed to isolate a possible trend in such highly volatile and rare events when accounting for several control variables - the higher the quantile, the higher the intrinsic volatility. Nevertheless, we can extract from our data some other useful information about human losses behavior adopting a slightly different perspective.

We adopt here a simple procedure for normalization of both human losses measure, i.e. dividing by country population (as explained in Equations B.4 and B.5 in Appendix B). Once deaths and affected people have been normalized, they can be plotted against each other so to investigate the evolution of observations in the deaths-affected space. We then perform a 2D kernel density estimation with only two bins in order to deal with over-plotting issues and provide a clear representation of any possible shift.

In Figure 7 we aggregate data by decade, income class and disaster type. Since storm and floods represent the vast majority of the observations (35% and 43%, respectively), we grouped together the remaining disaster types. Overall mass tends to move south-west, i.e. both deaths and people affected diminishing - consistently with negative global trend shown in Figure 6. Nevertheless, storm-related events display an increasingly evident polarization between rich and poor countries: south-west for high income counties (low deaths and affected), north-west for upper-income countries (low deaths, high affected), north-east for lower-middle countries (high deaths, high affected) and low income countries placed even more east (more deaths). Something similar happens for floods, with the only remarkable south-west movement (increasing adaptation) belonging exactly to high-income countries and the rest of the mass remaining more or less in the same region over time. Something completely opposite happens in the rest of the events (extreme temperatures, wildfires, landslides and droughts): a sharp south-west movement of low income countries can be easily spotted, due to the disappearance of huge humanitarian crisis (e.g. India's 1965 Drought which caused a famine killing 1.5 million people and affecting 100 millions); while lower-middle and upper-middle income countries remain stable, the only group moving north-east (towards more human losses) is that of rich countries.

Our disaggregated analysis appear to suggest that diminishing global trends found in Section 5.2

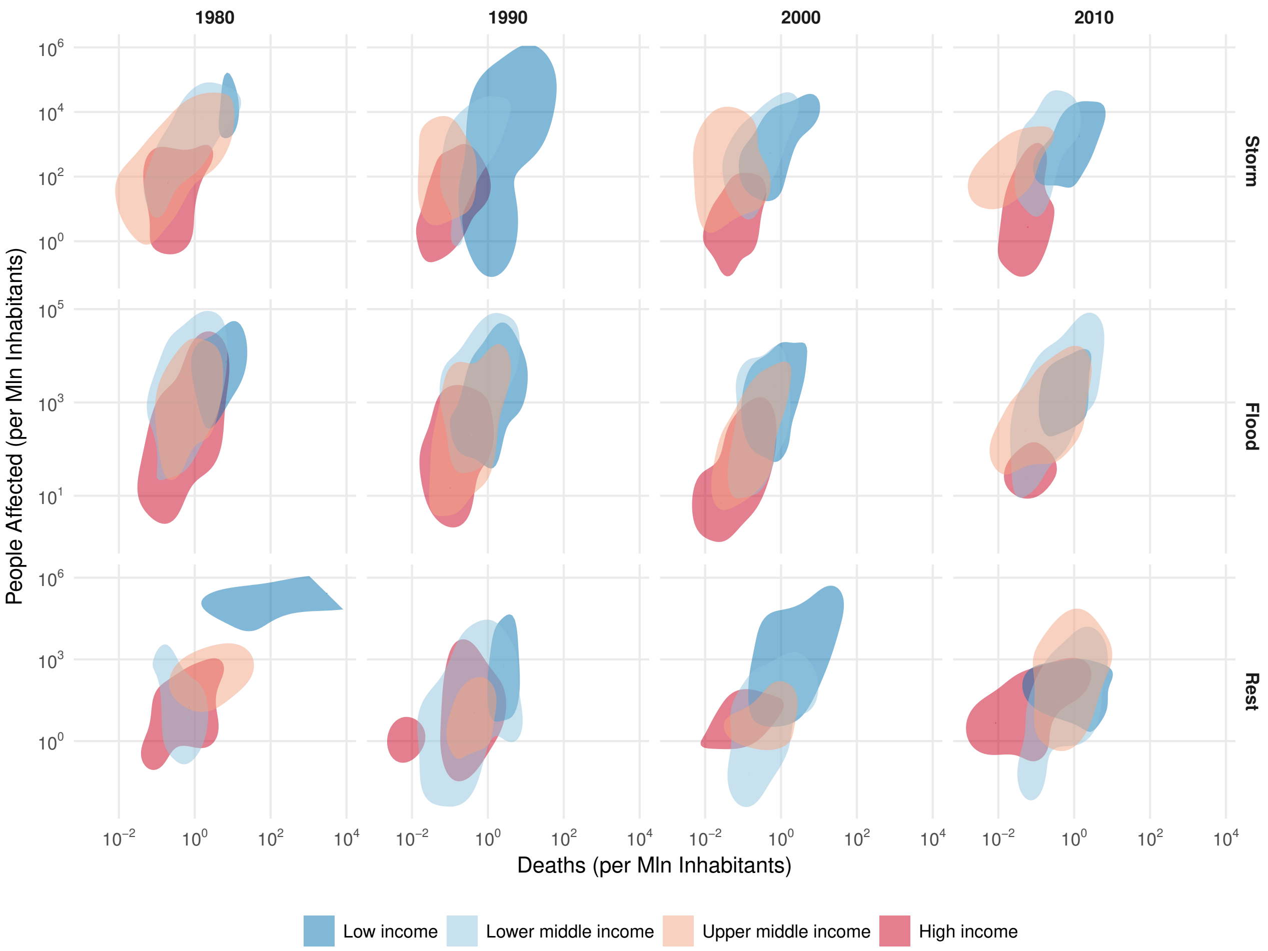

Figure 7: 2D kernel density estimates of events in the death/affected space, both measure normalized by population size. Data grouped by income level, by decade and type of hazard (extreme temperature, wildfire, drought and landslide grouped together under "Rest"). Axis-aligned bivariate normal kernel, evaluated on a square grid, 25 grid points in each direction. Number of bins forced to 2. Bandwidth is normal reference bandwidth (Venables and Ripley, 2002) in both directions. Time span 1960-2014.

are mostly due to the south-west movements in storm and flood events (the majority of recorded events), two types of natural hazards which have become more and more predictable over time and intrinsically give more room for adaptation policies with respect to other disasters such as extreme temperatures and wildfires. If avoiding human losses is getting easier for storm and floods, associated economic damages seem to increase at a dramatic pace (Table 2). As evacuation procedures clearly do not apply, e.g., to buildings, it is no surprise that human losses reduction is particularly evident in richer countries, while economic damages have skyrocketed.

We finally repeat the same exercise focusing on the geographical/climate zone perspective. By clustering observations in Köppen-Geiger climate zones (Figure 8) we observe that: (i) in temperate and arid zones, affected people have a fluctuating evolution both for storms and floods, while deaths tend to diminish over time (west movement), consistently with our interpretation; (ii) storms and

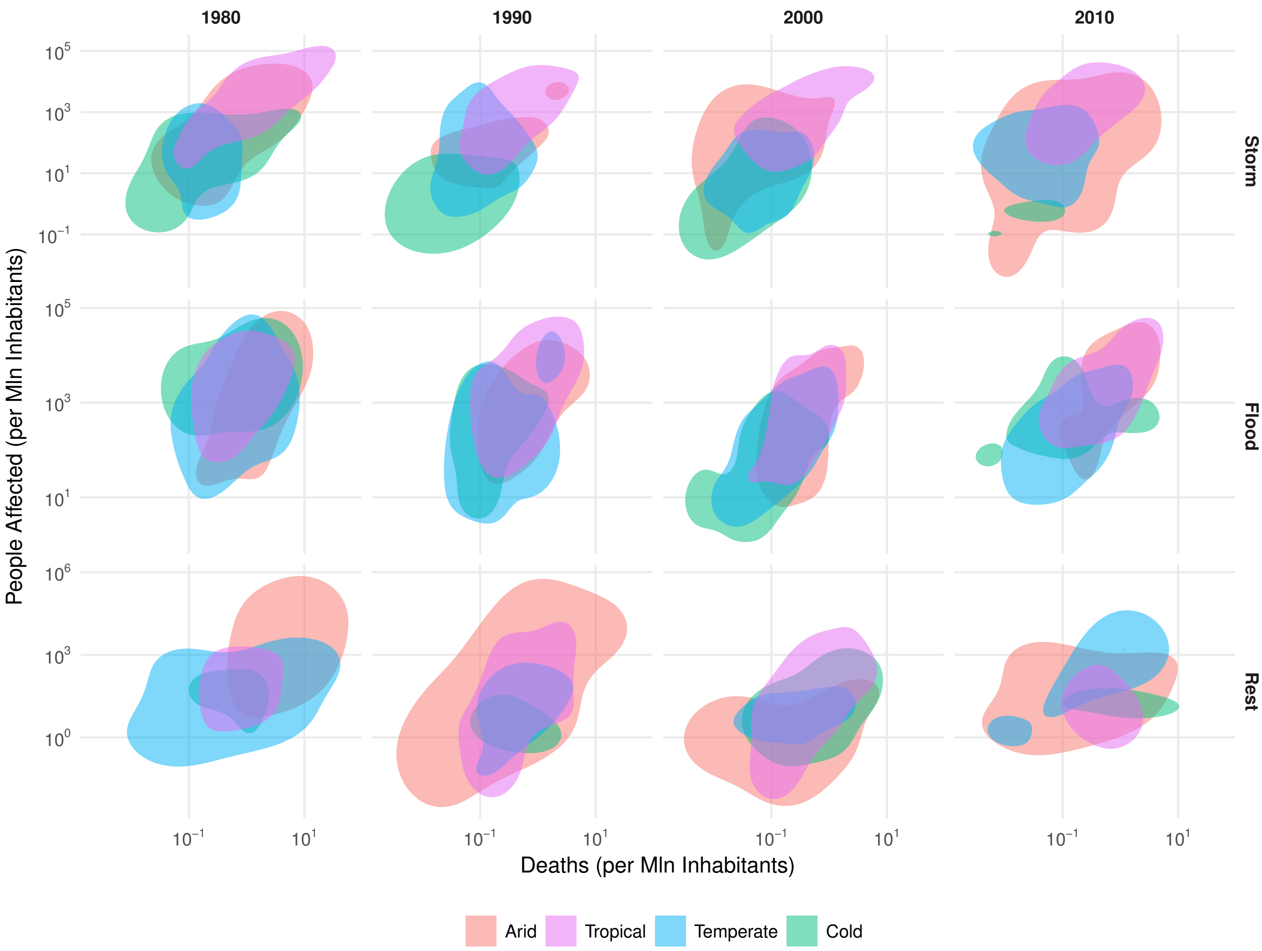

Figure 8: 2D kernel density estimates of events in the death/affected space, both measure normalized by population size. Data grouped by Köppen-Geiger climate zone, by decade and type of hazard (extreme temperature, wildfire, drought and landslide grouped together under ”Rest”). Axis-aligned bivariate normal kernel, evaluated on a square grid, 25 grid points in each direction. Number of bins forced to 2. Bandwidth is normal reference bandwidth (Venables and Ripley, 2002) in both directions. Time span 1960-2014.

floods events in cold zones tend to move south-west (both people killed and affected decreased), while tropical zones do not display any visible trend (with the possible exception of storms becoming slightly less deadly); (iii) for all non-storm and non-flood events the north-east shift concentrates in cold and temperate zones. We interpret this latter finding - coupled with the increasing trend showed in high and upper-middle income countries in Figure 7 - as mostly due to the increasing waves of extreme temperatures registered in Europe (see Appendix D).

6 Conclusions

In this work we have analyze the global evolution of losses (i.e., deaths, people affected, economic damages) relative to - climate-change potentially related - extreme weather events. Detection of a significant rising trend in losses is of paramount importance: when data are duly normalized, it can represent a trace of on-going climate change, and would thus call for urgent mitigation and adaptation policies to be but in place.

We propose a novel normalization procedure - ensuring spatial and temporal comparability of events - which genuinely tests for the presence of a pure time trend while allowing a non-linear impact of wealth to be present. Retaining the observational unit at the hazard level (i.e. not summing normalized data on a year basis) allow us to explore several features of loss distribution and their evolution over time, in particular high quantiles. Such a perspective is more informative about increased natural hazard risk, given the extremely skewed nature of associated losses. For these reason, we perform non-parametric kernel estimation of the damages distributions and we estimate a battery of quantile regressions.

Our results provide good news for human losses: both deaths and people affected exhibit a global downward trend, more intense in upper quantiles of their distribution. Such pattern is due to the disappearance of huge outliers (and to population dynamics in the case of affected), most likely the result of increased mitigation/adaptation efforts. However, we also document a worrying increasing polarization between income classes, with global diminishing trend most likely due to rich countries adaptation. Moreover, most of the global shift is attributable to storm and flood, i.e. the most predictable phenomena among those under consideration, while rising human losses are documented for e.g. extreme temperatures - mostly in temperate areas. Biases present in the dataset might also be relevant for the analysis of human losses.

On the contrary, the analysis carried out on the evolution of global damages provides a rather alarming picture. Our results indicate the existence of a positive global trend in upper quantiles of economic damages distribution with the estimated magnitude of per-year increment being increasing along quantiles. These findings appear to be robust to several model specifications, and biases present in the data are likely to make our estimates even conservative. The magnitude of the estimated trend is still quite noticeable: referring to the baseline model (C.1, Appendix C), considering an average of 149 recorded events per year (in the current decade), losses associated with disasters in the 99th percentile are estimated to increase each year by 39.32 Million \$. We report a stronger upsurge of damages in high income countries (although the increase is quite generalized). On the climatic perspective, the rise is particularly vigorous in tropical zones, and even more so in temperate ones.

Our results indicate that the distribution of damages is progressively shifting to the right, with a fattening right tail. Huge losses from major catastrophic hazards are getting bigger over time or more likely to happen. This suggests that signals of on-going climate change lies in the tails. The anemic results typically obtained in the literature on trend detection are due to their focus on mean regression, which only palely reflects meaningful changes on the right end of the distribution.

Beside the serious indication for policy-makers to adopt compelling and non-deferrable adaptation and mitigation policies, our results can have relevant implications for damage functions of most Integrated Assessment Models (IAMs), which have been criticized for their inability to account for major disasters when temperature anomaly gets significantly large (Ackerman et al., 2012; Weitzman, 2009). In that damage functions adopted in agent-based IAMs (Lamperti et al., 2018) could be a promising alternative and this work could allow to achieve a better, more data-driven, parametrization.

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Appendix A Data Treatment

Over the considered time span (1960-2015), lots of countries changed their political boundaries. Some countries were separate before a certain date and then merged together, some other split. In order to ensure proper over-time comparability to every unit of analysis, we grouped such countries as follows:

- Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania,the Republic of Moldova, the Russian Federation , Tajikistan, Turkmenistan, Ukraine and Uzbekistan have been grouped under Soviet Union.
- Serbia e Montenegro have been grouped under Serbia Montenegro.
- Bosnia and Herzegovina, Croatia, the former Yugoslav Republic of Macedonia, Serbia Montenegro and Slovenia have been grouped under Yugoslavia.
- Slovakia and the Czech Republic have been grouped under Czechoslovakia.
- Germany Democratic Republic and Germany Federal Republic have been grouped under Germany.
- Yemen Arab Republic and Yemen Democratic Republic have been grouped under Yemen.
- State of Palestine has been grouped under Israel.
- Timor-Leste has been grouped under Indonesia.
- Eritrea has been grouped under Ethiopia.

For what concern data from Penn World Table, we had to rule out observations occurred in 2015, as PWT contains data only until 2014. Some countries do not have data on GDP, at least in some years. Those observations have been excluded from the database when considering normalized measures of loss and in quantile regressions, for a total of 683 observations. Here is the list of such countries, with the number of observations removed between parenthesis: Afghanistan (121), American Samoa (5), Azores Islands (3), Canary Islands (7), Cook Islands (11), Cuba (74), Czechoslovakia (9), Eritrea (6), French Guiana (2), French Polynesia (7), Germany Democratic Republic (3), Guadeloupe (13), Guam (9), Guyana (10), Kiribati (5), the Democratic People's Republic of Korea (36), Libya (2), Marshall Islands (4), Martinique (14), Micronesia (8), Netherlands Antilles (4), New Caledonia (16), Niue (5), Northern Mariana Islands (3), Palau (1), Papua New Guinea (37), Puerto Rico (29), Reunion (11), Saint Helena (1), Samoa (13), Solomon Islands (25), Somalia (60), South Sudan (12), Soviet Union (30), Timor-Leste (8), Tokelau (6), Tonga (16), Tuvalu (7), Vanuatu (30), Virgin Island (6), Wallis and Futuna (4), Yugoslavia (10).

Country classification by income level: We used the classification provided by the World Bank. As of 1 July 2016, low-income economies are defined as those with a Gross National Income (GNI) per capita, calculated using the World Bank Atlas method, of $1,025 or less in 2015; lower middle-income economies are those with a GNI per capita between $1,026 and $4,035; upper middle-income economies are those with a GNI per capita between $4,036 and $12,475; high-income economies are those with a GNI per capita of $12,476 or more.

Data has been geolocalized thorough Google Maps API, using the location information present in the original dataset. Those observation which do not contain any useful information has been assigned with latitude and longitude of the centroid of the polygon formed by the relative country. Such observations are 1477 out of 10901 in the original dataset, 1265 out of 9495 once merging EM-DAT with PWT.

Koppen Climate Zones are recovered using geolocalized data merged with raster data provided in Kottek et al. (2006). Out of 10901 original observations, 452 did not found a point-to-cell match. In such cases, we assigned to the point the most frequent climatic zone among those in the 8 surrounding cells (as chess King's moves) plus the L-shaped "Knight's moves". Remaining 371 observations have been covered with the same procedure with raster data provided by Peel et al. (2007).

Appendix B Issues with Normalization

Normalization is required to compare the impact of natural disasters across time and space. Intuitively, the same building is worth more dollars today than in the 1950s and, at least partially, because of inflation; further, the number of deaths from its of destruction might depend on how many people live therein.

Losses have been usually quantified in terms of (i) monetary losses and (ii) people affected (or dead) by the particular hazard. With regard to the second measure, the normalization is straightforward and simply corrects for population density. Accordingly, the *share of affected* during natural disaster i at time t can be obtained as:

$$\text{share of affected}_{i,t} = \frac{\text{Total affected during event } i \text{ at time } t}{\text{Total population in the area of the event } i \text{ at time } t}. \tag{B.1}$$

Such a representation can be found in a variety of studies and reports (UNISDR, 2009; Guha-Sapir et al., 2012; CRED, 2015; Visser et al., 2014). Other contributions, instead, prefer not to normalize and to focus on the absolute number of people affected by the disaster (see e.g. Toya and Skidmore, 2007). However, in our view, avoid to control for population size would increase the risk of incurring in a biased estimation of the damages, which would not be comparable across time and space.

To prevent from such problems, the normalization of economic losses has received larger attention in the literature. The conventional approach to normalizing natural disaster losses can be traced back to Pielke and Landsea (1998) and Pielke et al. (1999) and expressed through the following equation:

$$\text{normalized loss}_{i,t}^{ref} = \text{Loss}_{i,t} \frac{\text{GDP deflator}_{i,ref} \cdot \text{Population}_{i,ref} \cdot \text{Wealth per capita}_{i,ref}}{\text{GDP deflator}_{i,t} \cdot \text{Population}_{i,t} \cdot \text{Wealth per capita}_{i,t}} \tag{B.2}$$

where i indicates the disaster occurred in a given area, ref stands for the reference year and t the year of occurrence. The Gross Domestic Product (GDP) deflator adjusts for inflation (i.e. changes in prices), while the remaining two correction factors adjust for changes in population and wealth per capita. According to Pielke et al. (2008) such procedure provides "longitudinally consistent estimates of the economic damage" that past disasters would have caused "under contemporary levels of population and development". The conventional approach has been widely used in the literature, despite the main problem of obtaining reliable wealth data. Brooks and Doswell (2001) and Vranes and Pielke (2009) used the value of capital stocks; Crompton and McAneney (2008) and Pielke et al. (2008) the one of dwellings, while many others simply relied on GDP (Raghavan and Rajesh, 2003; Nordhaus, 2006; Barredo, 2009).

Beyond the data-quality issue, Neumayer and Barthel (2011) pointed out that the conventional approach is incomplete. On one hand it adjusts for changes in wealth and population over time but, on the other, it fails to adjust for differences in wealth and population across space at any given point of time.[14] To use the example of the authors, "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. 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". Putting it shortly, equation (B.2) cleans for the rate of growth of confounding factors, but not for their size. Neumayer and Barthel (2011) have thus proposed the following approach to normalization:

$$\text{normalized loss}_{i,t} = \frac{\text{Loss}_{i,t}}{\text{Wealth}_{i,t}}, \tag{B.3}$$

which implies that each loss is expressed as the share the theoretical total destroyable wealth that has been effectively lost and can therefore be interpreted as an actual-to-potential-loss (APLR) ratio. Such a procedure would adjust for differences across space: by dividing actual damage by the wealth in affected areas that can potentially be destroyed it controls 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. Further, since a relative damage is time-invariant is also directly comparable across years. Such an approach has been applied to insured disaster data (Barthel and Neumayer, 2012), to enable comparison of impacts across disasters in small states, islands or counties (Noy, 2009; Ash et al., 2013) and between disasters in Japan, Pakistan, and the USA (Gardoni and Murphy, 2010) and, more recently, to estimate the impact of climate change and vulnerability on disaster-related damages (Visser et al., 2014).

[14] We notice that the conventional approach also fails to account for population dynamics since the population variable in equation (B.2) is ruled out by the use of the per-capita wealth.

Despite its features the Neumayer and Barthel (2011)'s normalization fails to solve the wealth data availability problem and, more relevantly, does not account for population dynamics. However, it is likely that more populated areas exhibit higher total wealth and, in addition, that areas with higher population growth experience higher GDP and wealth growth as well. For these reasons, we believe normalization should somehow correct for these effects. Here we present descriptive evidences coming out from different loss normalizations to show that they do not contradict our main findings.

To do so we take advantage of the Penn World Table dataset (Feenstra et al., 2015). While the unit of analysis is retained at the observational level, normalization measures are at the country level [15]; time unit is year. Keeping the unit of analysis at the event level, compared to yearly or multi-year aggregation, has the advantage of being able to exploit the various feature of the within year distribution of damages (which is valuable information). More importantly, as already pointed out, focus on distributions substantially reduce underreporting bias.

$$\text{Normalized Deaths}_{i,t} = \frac{\text{Deaths}_{i,t}}{\text{Population}_{i,t}} \tag{B.4}$$

$$\text{Normalized Affected}_{i,t} = \frac{\text{People Affected}_{i,t}}{\text{Population}_{i,t}} \tag{B.5}$$

$$\text{Normalized Economic Damage}_{i,t} = \frac{\text{Economic Damage}_{i,t}}{\text{GDP per capita}_{i,t}} \tag{B.6}$$

The intuitive normalization for death and affected people is carried out by dividing for the total population of the relative country, as already shown in equation B.1. For what concern economic damages some clarifications are needed. We follow the ATPL approach suggested by Neumayer and Barthel (2011): to ensure spatial comparability, we simply divide the damage (at current PPP, U.S.A. Dollars) by a measure of wealth. Penn World Table 9.0 offer us two suitable measures for wealth: GDP (at current PPP, U.S.A. Dollars) and capital stock (at current PPP, U.S.A. Dollars). We are going to make use of both, as they can shed light on different aspect of economic harms produced by natural disasters. In both cases, the PPP ensure spatial comparability within years, while the ratio between two values expressed in current terms originate an a-dimensional measure which can be compared over time. Unlike Neumayer and Barthel (2011), we choose to use per capita wealth measures: as population size mechanically affect GDP (and capital), both in spatial and chronological terms, we argue that it is crucial for a proper analysis to control for that effect.

Figure B.1, B.2 and B.3 provide insights into the evolution of normalized quantities following equations (B.4), (B.5) and (B.6). Figures B.4 and B.5 present results from OLS regression on yearly summed data for economic damages, following three different procedures: (i) and (ii) by normalizing observations through equations (B.3) and (B.4) respectively, (iii) by summing observation and normalization factors before computing the ratio. The latter approach is also discussed in Neumayer and Barthel (2011), arguing that results are pretty similar to those obtained with (i), altough (iii) is in principle more tail sensitive. Results using a restricted time sample starting from the 80's are reported to ensure full comparability with Neumayer and Barthel (2011).

Finally, we notice that our approach (eqs. 1-3 in the main text) provides a generation of the APL methodology adopted in Neumayer and Barthel (2011), who normalize monetary damages using the GDP of the area affected by the disaster, a proxy for the maximum potentially destroyable wealth. Once damages have been normalized, the presence (or absence) of a trend is detected estimating a model of the following type:

$$\frac{\text{Damage}_{it}}{\text{GDP}_{it}} = \text{Normalized Damage}_{it} = a + b \cdot \text{Trend}_t. \tag{B.7}$$

Now, one can see that our specification (3) encompasses such a linear model (equation (B.7)) by simply adding the interaction term between Trend_t and GDP_{it} in the control set $\mathbf{x}_{it}'''$:

$$\text{Damage}_{it} = \alpha_3 + \beta_3 \text{Trend}_t + \gamma_3 \text{GDP}_{it} + \theta\, \text{Trend}_t \cdot \text{GDP}_{it}, \tag{B.8}$$

and exogenously restricting (B.8) by imposing $\alpha_3 = \beta_3 = 0$ to obtain (B.7).

Interestingly, we also notice

[15] See Appendix A for details on issues with PWT and on treatment of countries over time.

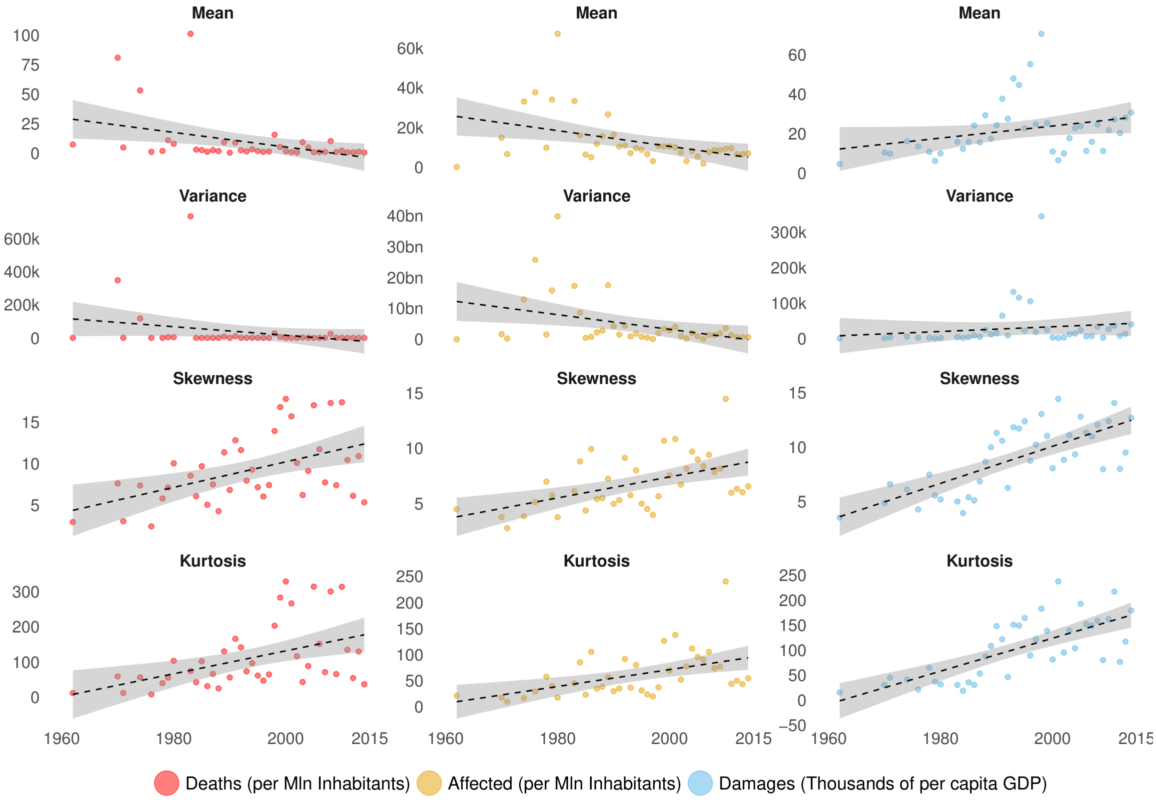

Figure B.1: Summary of yearly normalized losses distributions based on moments, by type of loss. Dashed lines are OLS trend estimates. Time span: 1960-2014.

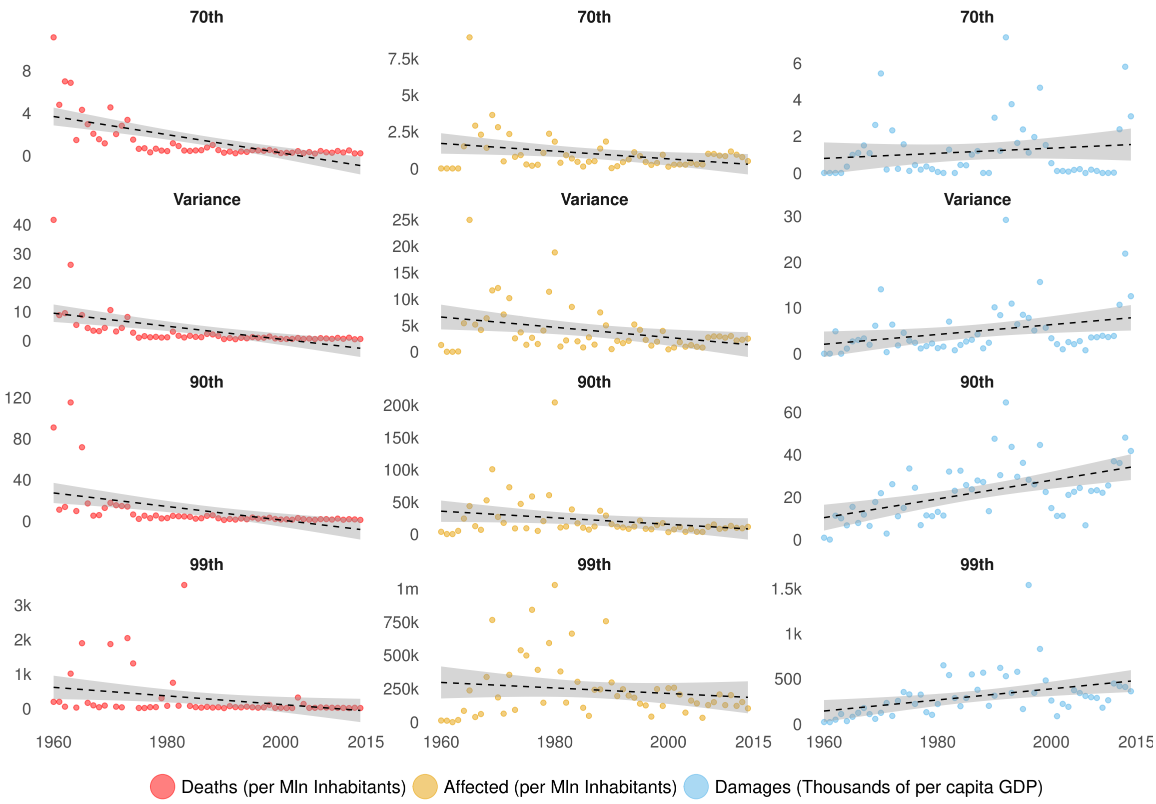

Figure B.2: Selected quantiles of yearly normalized losses distributions, by type of loss. Dashed lines are OLS trend estimates. Time span: 1960-2014.

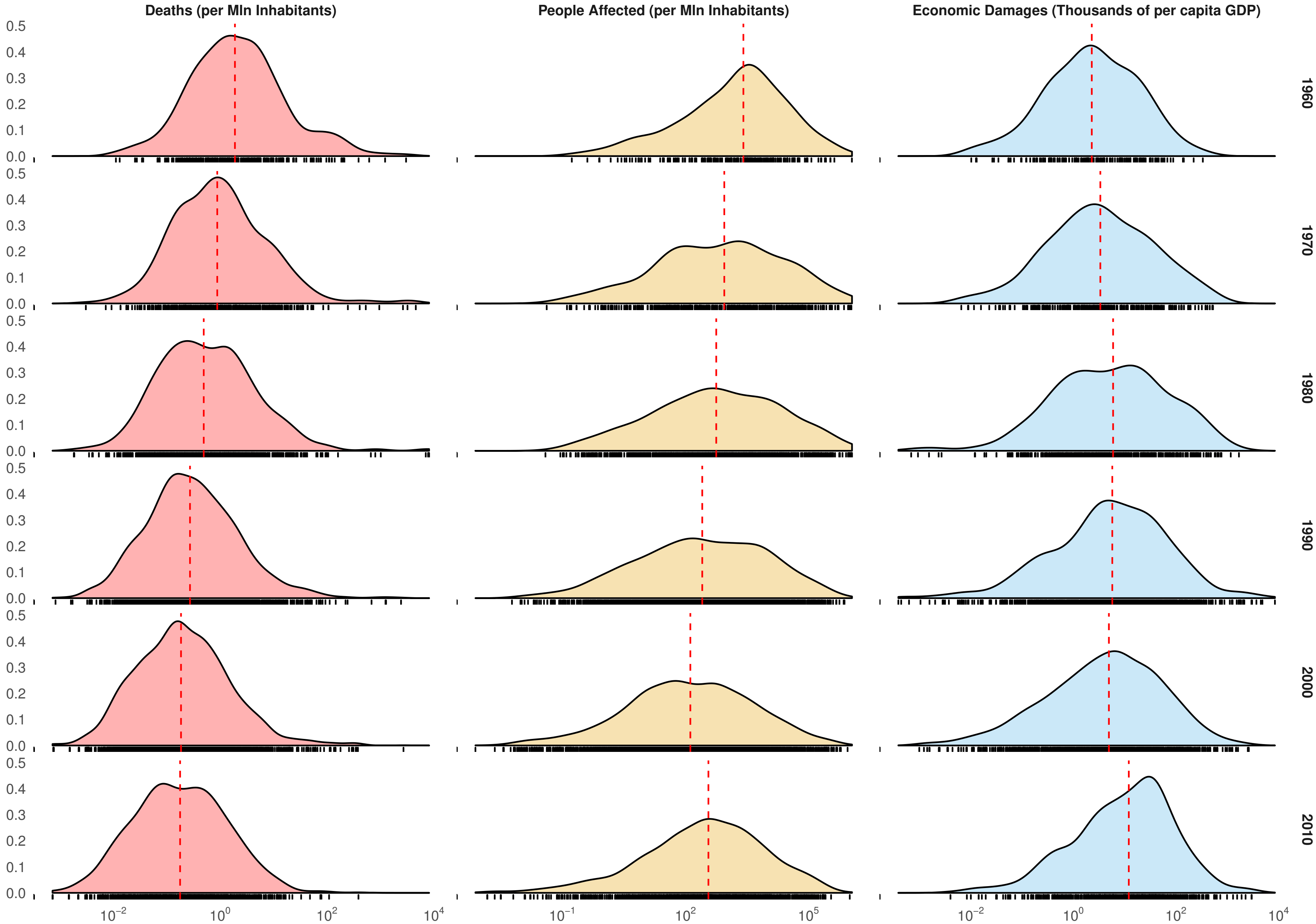

Figure B.3: Normalized loss kernel density estimates, by type of loss. Data aggregated on a decade basis. Horizontal log-axis. Dashed red lines represent medians. Zero losses disasters excluded from computations. Kernel is Gaussian. Bandwidth selection is done by Silverman's rule-of-thumb (Silverman, 1986), i.e. 0.9 times the minimum of the standard deviation and the interquartile range divided by 1.34 times the sample size to the negative one-fifth power. Rug plots below each distribution represent marginal distributions. Time span 1960-2014.

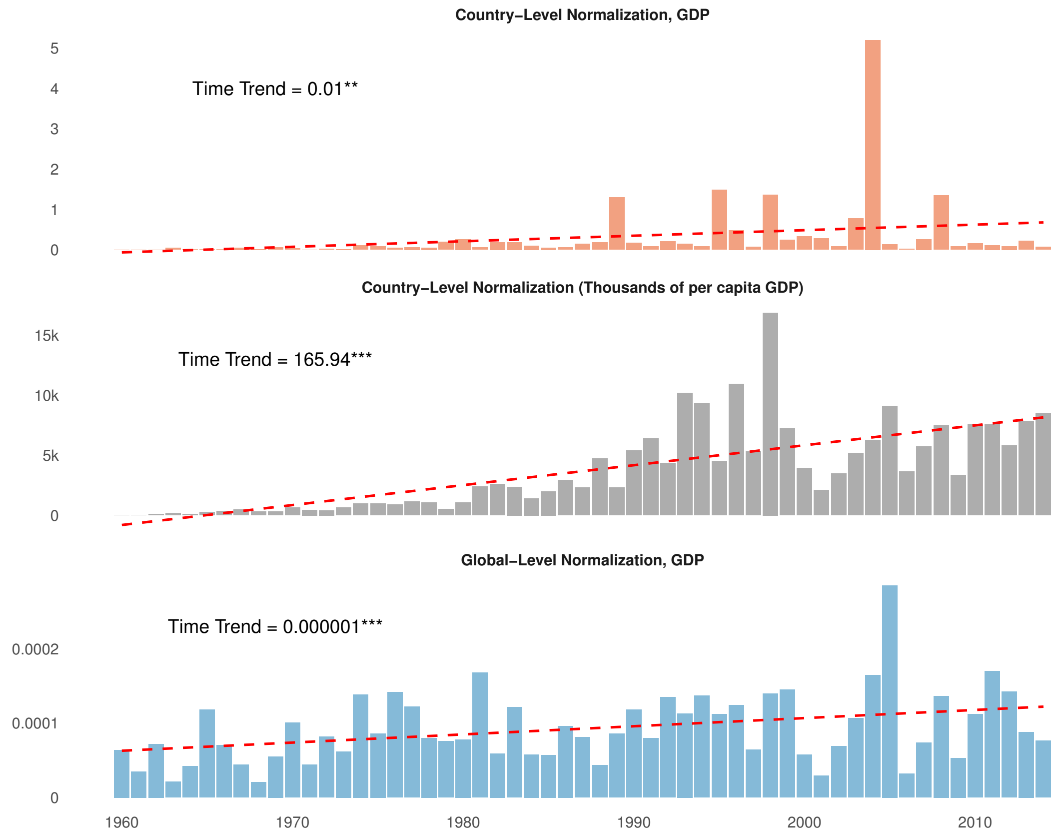

Figure B.4: Yearly global sum of economic damages, by type of normalization. Dashed lines are OLS trend estimates. p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed. Time span: 1960-2014.

Figure B.5: Yearly global sum of economic damages, by type of normalization. Dashed lines are OLS trend estimates. p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed. Time span: 1980-2014.

Appendix C Robustness

This section gathers all the regression performed. In particular, in addition to baseline regression presented in Figure 6, we provide alternative model specifications and experiment with varying time span.

Table C.1: Robustness analysis for economic damages. Quantile regressions estimates for selected quantiles and OLS estimates on economic damages (except for model (6) where economic damages over GDP is the dependent variable). Covariates on first column. Method is modified Barrodale-Roberts algorithm (Koenker and d'Orey, 1987)). Bootstrapped standard errors according to x-y pairwise resampling algorithm, as recommended in Efron and Tibshirani (1994). p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed.

	Variable	70th	80th	90th	95th	99th	OLS
(1) 1960-2014	Intercept	0.466**	6.679***	20.755*	37.818	94.15	-38.368
		(0.21)	*(2.133)*	*(10.782)*	*(42.002)*	*(109.263)*	*(56.267)*
	Trend	-0.016***	-0.137***	1.226***	4.797***	26.385***	2.536*
		(0.005)	*(0.044)*	*(0.403)*	*(1.305)*	*(6.847)*	*(1.472)*
	GDP	0.023***	0.062***	0.148***	0.298***	1.251***	0.076***
		(0.002)	*(0.006)*	*(0.015)*	*(0.042)*	*(0.289)*	*(0.005)*
(1) 1970-2014	Intercept	0.335	8.962**	60.114***	191.829***	431.572***	-17.857
		(0.224)	*(3.543)*	*(18.399)*	*(64.672)*	*(146.034)*	*(52.669)*
	Trend	-0.018***	-0.233***	0.262	1.402	22.933***	2.677
		(0.006)	*(0.086)*	*(0.658)*	*(2.291)*	*(8.188)*	*(1.766)*
	GDP	0.023***	0.062***	0.149***	0.301***	1.255***	0.076***
		(0.002)	*(0.007)*	*(0.015)*	*(0.044)*	*(0.268)*	*(0.005)*
(1) 1980-2014	Intercept	0.159	10.225**	87.104***	248.78***	788.962***	0.213
		(0.148)	*(4.055)*	*(17.758)*	*(57.518)*	*(277.784)*	*(50.14)*
	Trend	-0.018***	-0.349***	-0.8	-0.527	17.551	3.025
		(0.006)	*(0.127)*	*(0.97)*	*(2.891)*	*(14.117)*	*(2.284)*
	GDP	0.023***	0.061***	0.15***	0.301***	1.253***	0.076***
		(0.002)	*(0.007)*	*(0.015)*	*(0.047)*	*(0.276)*	*(0.005)*
(2) 1960-2014	Intercept	1.893*	0	0	0	35	-57.017
		(1.008)	*(1.642)*	*(3.774)*	*(12.151)*	*(206.191)*	*(56.146)*
	Trend	0.093***	1.42***	7.447***	21.852***	95.481***	7.105***
		(0.036)	*(0.145)*	*(0.482)*	*(1.33)*	*(10.19)*	*(1.442)*
(2) 1970-2014	Intercept	3.904**	12.409**	37.895*	125**	411.613	-6.185
		(1.552)	*(5.265)*	*(22.119)*	*(48.979)*	*(264.328)*	*(53.172)*
	Trend	0.052	1.486***	8.737***	25***	118.387***	7.739***
		(0.066)	*(0.29)*	*(0.991)*	*(2.78)*	*(16.086)*	*(1.751)*

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Table C.1: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(2) 1980-2014	Intercept	5.822***	32.5***	91***	321.538***	1326.364**	58.23
		(2.005)	*(8.615)*	*(32.213)*	*(64.901)*	*(565.097)*	*(50.553)*
	Trend	-0.016	1.25**	10.45***	27.308***	133.636***	8.297***
		(0.108)	*(0.552)*	*(1.819)*	*(4.36)*	*(35.576)*	*(2.281)*
(3) 1960-2014	Intercept	1.354**	11.704***	26.877**	43.557	93.663	-27.428
		(0.532)	*(3.569)*	*(13.446)*	*(38.412)*	*(98.025)*	*(56.557)*
	Trend	-0.029***	-0.202***	1.104**	4.815***	25.624***	2.54*
		(0.011)	*(0.074)*	*(0.432)*	*(1.308)*	*(6.635)*	*(1.472)*
	GDP	0.025***	0.069***	0.159***	0.316***	1.163***	0.081***
		(0.003)	*(0.007)*	*(0.019)*	*(0.055)*	*(0.338)*	*(0.006)*
	Population	-0.029***	-0.083 ***	-0.091	-0.205	0.796	-0.114*
		(0.004)	*(0.012)*	*(0.068)*	*(0.177)*	*(1.37)*	*(0.061)*
(3) 1970-2014	Intercept	1.104*	17.959***	73.005***	197.616***	406.634***	-5.627
		(0.613)	*(4.095)*	*(17.657)*	*(59.516)*	*(152.364)*	*(53.076)*
	Trend	-0.03*	-0.419***	-0.032	1.27	24.05***	2.643
		(0.016)	*(0.1)*	*(0.665)*	*(2.006)*	*(8.115)*	*(1.766)*
	GDP	0.026***	0.069***	0.161***	0.32***	1.161***	0.081***
		(0.003)	*(0.007)*	*(0.019)*	*(0.055)*	*(0.329)*	*(0.006)*
	Population	-0.03***	-0.089***	-0.101	-0.215	0.855	-0.115*
		(0.005)	*(0.013)*	*(0.073)*	*(0.197)*	*(1.822)*	*(0.062)*
(3) 1980-2014	Intercept	1.003	19.778***	99.011***	251.64***	783.248***	14.846
		(0.68)	*(5.616)*	*(19.602)*	*(53.714)*	*(270.797)*	*(50.802)*
	Trend	-0.037	-0.613***	-1.126	-0.661	18.239	2.88
		(0.024)	*(0.174)*	*(0.997)*	*(2.573)*	*(14.197)*	*(2.285)*
	GDP	0.026***	0.069***	0.161***	0.317***	1.162***	0.082***
		(0.003)	*(0.007)*	*(0.018)*	*(0.056)*	*(0.367)*	*(0.006)*
	Population	-0.03***	-0.095***	-0.144*	-0.214	0.801	-0.116*
		(0.005)	*(0.016)*	*(0.081)*	*(0.209)*	*(1.788)*	*(0.065)*
(4) 1960-2014	Intercept	-2.498***	-7.689***	-26.19***	-46.027***	-204.197***	-134.651**
		(0.359)	*(1.199)*	*(4.516)*	*(13.29)*	*(46.957)*	*(56.97)*
	Trend	-0.013*	0.041*	0.552**	4.41***	37.345***	3.92***
		(0.007)	*(0.024)*	*(0.255)*	*(1.055)*	*(8.476)*	*(1.477)*
	GDP per capita	2.626***	8.016***	29.576***	52.454***	197.189***	15.494***
		(0.21)	*(0.75)*	*(2.07)*	*(6.627)*	*(44.352)*	*(1.361)*

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Table C.1: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(5) 1960-2014	Intercept	3.01***	15.404***	31.023**	38.196	220.579	29.974
		(0.822)	*(3.044)*	*(14.066)*	*(54.229)*	*(258.583)*	*(61.525)*
	Trend	-0.072***	-0.317***	0.936**	4.795***	23.252**	0.885
		(0.018)	*(0.061)*	*(0.469)*	*(1.66)*	*(10.387)*	*(1.59)*
	GDP	-0.006***	0.005	0.093**	0.28***	0.747	0.01
		(0.002)	*(0.012)*	*(0.039)*	*(0.107)*	*(0.837)*	*(0.024)*
	Trend*GDP	0.001***	0.001***	0.001	0	0.011	0.001***
		(0.00009)	*(0.0003)*	*(0.001)*	*(0.003)*	*(0.021)*	*(0.001)*
(6) 1960-2014	Intercept	0.175***	0.784***	2.685***	7.194**	37.334	5.37
		(0.042)	*(0.134)*	*(0.84)*	*(3.173)*	*(29.762)*	*(26.369)*
	Trend	-0.002**	-0.002	0.066***	0.278***	2.285***	0.465
		(0.001)	*(0.004)*	*(0.024)*	*(0.095)*	*(0.804)*	*(0.676)*

Table C.2: Robustness analysis for people affected. Quantile regressions estimates for selected quantiles and OLS estimates on people affected. Covariates on first column. Method is modified Barrodale-Roberts algorithm (Koenker and d'Orey, 1987)). Bootstrapped standard errors according to x-y pairwise resampling algorithm, as recommended in Efron and Tibshirani (1994). p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed.

	Variable	70th	80th	90th	95th	99th	OLS
(1) 1960-2014	Intercept	7.317**	46.587***	251.707***	985.731***	4635.217***	621.94**
		(3.006)	*(10.685)*	*(52.402)*	*(190.572)*	*(1154.012)*	*(246.444)*
	Trend	0.025	-0.585**	-3.638***	-15.45***	-81.321***	-16.914***
		(0.07)	*(0.238)*	*(1.175)*	*(4.232)*	*(22.578)*	*(6.335)*
	Population	0.151***	0.699***	4.093***	12.538***	78.955***	3.812***
		(0.021)	*(0.132)*	*(0.606)*	*(1.871)*	*(14.585)*	*(0.226)*
(1) 1970-2014	Intercept	4.917**	37.506***	261.967***	993.388***	3918.583***	620.013***
		(2.382)	*(10.03)*	*(64.773)*	*(223.328)*	*(842.283)*	*(229.384)*
	Trend	0.098	-0.524*	-5.011***	-20.395***	-83.63***	-22.102***
		(0.072)	*(0.274)*	*(1.724)*	*(5.99)*	*(19.689)*	*(7.532)*
	Population	0.153***	0.726***	4.131***	12.577***	78.823***	3.804***
		(0.02)	*(0.13)*	*(0.48)*	*(2.139)*	*(14.136)*	*(0.23)*
(1) 1980-2014	Intercept	3.483*	29.543***	214.517***	747.409***	3599.584***	445.231**
		(1.985)	*(8.705)*	*(53.569)*	*(179.368)*	*(955.835)*	*(210.791)*
	Trend	0.188**	-0.411	-5.011***	-18.18***	-100.287***	-23.151**
		(0.083)	*(0.323)*	*(1.86)*	*(6.616)*	*(27.624)*	*(9.368)*
	Population	0.155***	0.726***	4.016***	12.085***	78.664***	3.716***
		(0.022)	*(0.132)*	*(0.506)*	*(2.078)*	*(16.045)*	*(0.232)*

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Table C.2: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(2) 1960-2014	Intercept	14.565***	72.441***	396.667***	1500***	16134.867***	915.517***
		(3.311)	*(13.266)*	*(83.721)*	*(312.503)*	*(6013.169)*	*(245.881)*
	Trend	0.109	0.014	0.185	0	-106.973	-4.887
		(0.08)	*(0.328)*	*(2.074)*	*(8.319)*	*(148.618)*	*(6.314)*
(2) 1970-2014	Intercept	13.736***	67.431***	452.458***	1845***	18060.476***	1047.654***
		(3.28)	*(14.661)*	*(82.387)*	*(378.201)*	*(5610.535)*	*(230.69)*
	Trend	0.158	0.142	-1.319	-10.75	-187.316	-10.55
		(0.104)	*(0.455)*	*(2.626)*	*(11.976)*	*(170.897)*	*(7.597)*
(2) 1980-2014	Intercept	14.63***	69.769***	486.1***	1731.297***	18934.783***	1048.634***
		(3.326)	*(11.318)*	*(77.732)*	*(310.845)*	*(4567.733)*	*(210.38)*
	Trend	0.185	0.116	-3.244	-10.13	-304.348*	-14.964
		(0.135)	*(0.477)*	*(3.295)*	*(12.423)*	*(179.099)*	*(9.491)*
(3) 1960-2014	Intercept	0.772	23.112**	145.142***	622.935***	3820.792***	529.896**
		(2.211)	*(9.723)*	*(45.166)*	*(184.634)*	*(1187.591)*	*(246.746)*
	Trend	0.231***	0.084	-0.641	-6.773	-59.452**	-11.166*
		(0.057)	*(0.25)*	*(1.09)*	*(4.196)*	*(23.493)*	*(6.423)*
	Population	0.266***	1.165***	5.633***	17.001***	93.087***	4.515***
		(0.045)	*(0.234)*	*(0.75)*	*(2.919)*	*(21.667)*	*(0.264)*
	GDP	-0.006***	-0.025***	-0.118***	-0.351***	-1.84***	-0.129***
		(0.001)	*(0.004)*	*(0.014)*	*(0.054)*	*(0.408)*	*(0.025)*
(3) 1970-2014	Intercept	0.082	14.857*	151.65***	634.337***	3297.616***	560.058**
		(1.568)	*(8.076)*	*(42.646)*	*(179.912)*	*(949.575)*	*(229.389)*
	Trend	0.316***	0.318	-1.167	-9.475*	-61.468***	-15.66**
		(0.05)	*(0.236)*	*(1.341)*	*(5.142)*	*(22.31)*	*(7.632)*
	Population	0.267***	1.182***	5.741***	16.996***	93.081***	4.498***
		(0.051)	*(0.236)*	*(0.757)*	*(2.849)*	*(20.026)*	*(0.269)*
	GDP	-0.006***	-0.025***	-0.12***	-0.349***	-1.839***	-0.127***
		(0.001)	*(0.004)*	*(0.014)*	*(0.054)*	*(0.373)*	*(0.025)*
(3) 1980-2014	Intercept	-0.077	11.427	115.269***	409.164***	2877.053***	427.948**
		(1.182)	*(7.548)*	*(32.225)*	*(139.241)*	*(933.301)*	*(210.546)*
	Trend	0.444***	0.606**	-0.082	-3.389	-71.394**	-16.156*
		(0.062)	*(0.289)*	*(1.342)*	*(5.289)*	*(28.801)*	*(9.471)*
	Population	0.281***	1.176***	5.475***	16.452***	93.067***	4.386***
		(0.047)	*(0.22)*	*(0.844)*	*(3.275)*	*(18.522)*	*(0.271)*
	GDP	-0.006***	-0.025***	-0.115***	-0.342***	-1.83***	-0.121***
		(0.001)	*(0.004)*	*(0.015)*	*(0.061)*	*(0.351)*	*(0.026)*

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Table C.2: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(7) 1960-2014	Intercept	-0.26***	-1.248**	-7.795**	2.963	0.388	-191.741
		(0.086)	*(0.527)*	*(3.056)*	*(12.375)*	*(15.512)*	*(421.847)*
	Trend	-0.016***	-0.052**	-0.156**	-0.395	-0.057	-4.245
		(0.005)	*(0.023)*	*(0.065)*	*(0.317)*	*(0.369)*	*(11.211)*
	Population	0.11***	0.511***	3.7***	11.612***	79.227***	3.711***
		(0.022)	*(0.146)*	*(0.521)*	*(2.098)*	*(13.228)*	*(0.237)*
	Low	165.734***	664.474***	1781.494***	2934.424***	6737.37***	716.152
		(44.399)	*(142.212)*	*(272.745)*	*(1038.975)*	*(1505.417)*	*(941.768)*
	Lower-Mid.	111.449***	343.448***	1266.318***	3037.499***	12898.44	1983.826***
		(31.441)	*(80.123)*	*(339.541)*	*(758.68)*	*(8488.664)*	*(600.097)*
	Upper-Mid.	21.924***	66.631***	168.605***	363.538	1991.597	576.807
		(7.509)	*(21.167)*	*(50.719)*	*(237.538)*	*(1530.529)*	*(654.784)*
	Trend*Low	-2.573***	-11.744***	-29.559***	-41.943*	-87.724*	-3.194
		(0.924)	*(3.005)*	*(6.571)*	*(24.619)*	*(45.394)*	*(23.507)*
	Trend*Lower	-0.896	-3.186*	-17.444**	-45.884***	-239.115	-38.345**
		(0.703)	*(1.898)*	*(7.558)*	*(16.326)*	*(160.125)*	*(15.689)*
	Trend*Upper	-0.143	-0.763	-2.041*	-4.455	-32.678	-3.419
		(0.166)	*(0.471)*	*(1.209)*	*(5.361)*	*(35.069)*	*(16.848)*
(8) 1960-2014	Intercept	70.155***	213.319***	810.595***	2272.737***	7390.086**	843.846**
		(19.311)	*(56.708)*	*(215.526)*	*(526.653)*	*(3234.173)*	*(392.506)*
	Trend	-0.475	-1.985	-11.081**	-36.738***	-133.81**	-21.617**
		(0.452)	*(1.417)*	*(4.934)*	*(12.276)*	*(62.223)*	*(10.081)*
	Population	0.133***	0.606***	4.076***	12.122***	79.329***	3.817***
		(0.023)	*(0.144)*	*(0.531)*	*(1.859)*	*(15.556)*	*(0.23)*
	Arid	-22.748	-77.501	-258.74	-840.852	3557.975	987.07
		(24.044)	*(74.769)*	*(374.042)*	*(716.261)*	*(21120.534)*	*(780.405)*
	Cold	-71.974***	-219.383***	-842.517***	-2353.992***	-7078.74**	-1064.478
		(19.276)	*(56.682)*	*(215.601)*	*(524.195)*	*(3200.946)*	*(1078.828)*
	Temperate	-70.776***	-214.283***	-806.978***	-2257.998***	-5916.004*	-669.426
		(19.306)	*(56.727)*	*(215.417)*	*(534.465)*	*(3313.526)*	*(550.854)*
	Polar	-72.833***	-217.159***	-801.042***	-2211.32***	-7392.216**	-1547.555
		(19.671)	*(56.513)*	*(217.469)*	*(540.655)*	*(3414.343)*	*(2317.75)*
	Trend*Arid	-0.151	0.363	4.982	28.916	-50.029	-19.539
		(0.552)	*(1.904)*	*(8.787)*	*(19.634)*	*(408.444)*	*(19.965)*
	Trend*Cold	0.503	2.058	11.482**	37.751***	125.803**	16.203
		(0.452)	*(1.417)*	*(4.943)*	*(12.31)*	*(62.922)*	*(27.49)*
	Trend*Temper.	0.485	1.979	10.852**	36.205***	109.255*	15.492
		(0.452)	*(1.415)*	*(4.932)*	*(12.457)*	*(64.948)*	*(14.175)*
	Trend*Polar	0.553	2.043	10.336**	33.944**	133.266*	12.802
		(0.474)	*(1.406)*	*(4.985)*	*(14.495)*	*(69.429)*	*(59.811)*

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Table C.2: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(9) 1960-2014	Intercept	-0.301	5.548	39.684	188.659	1074.484*	-186.175
		(0.744)	*(5.011)*	*(29.293)*	*(115.71)*	*(563.901)*	*(387.604)*
	Trend	0.03	-0.042	-0.329	-3.587	-21.171*	-10.477
		(0.024)	*(0.124)*	*(0.768)*	*(2.549)*	*(11.738)*	*(10.328)*
	Population	0.138***	0.645***	3.981***	11.726***	77.716***	4***
		(0.023)	*(0.133)*	*(0.554)*	*(1.853)*	*(15.703)*	*(0.226)*
	Drought	46.827	634.543*	2372.501*	4186.458	70088.958	4361.594***
		(242.248)	*(370.459)*	*(1362.813)*	*(6078.071)*	*(66283.1)*	*(911.671)*
	Extreme T.	-12.89***	-33.419***	-105.563***	-304.253**	-991.822	-1329.936
		(3.815)	*(11.9)*	*(35.859)*	*(129.753)*	*(1568.822)*	*(1469.726)*
	flood	39.879***	116.119***	243.685***	795.928***	3121.33	1022.038*
		(7.383)	*(25.087)*	*(70.648)*	*(296.247)*	*(2370.75)*	*(553.518)*
	Landslide	-0.167	-7.465	-47.375	-190.716	-880.968	255.889
		(0.883)	*(5.049)*	*(30.249)*	*(120.07)*	*(618.948)*	*(1037.935)*
	Wildfire	0.366	-6.697	-52.044*	-217.564*	-1097.523*	212.997
		(0.805)	*(5.029)*	*(30.432)*	*(114.95)*	*(572.299)*	*(1423.281)*
	Trend*Drought	24.972***	37.262***	50.608	81.927	-1247.911	-16.484
		(7.941)	*(14.051)*	*(45.94)*	*(159.827)*	*(1515.776)*	*(25.212)*
	Trend*Extreme	0.236***	0.584**	1.502*	5.736*	19.699	33.013
		(0.089)	*(0.28)*	*(0.906)*	*(2.965)*	*(33.812)*	*(34.703)*
	Trend*Flood	-0.407**	-1.723***	-4.025**	-14.653**	-59.362	-7.799
		(0.169)	*(0.57)*	*(1.593)*	*(6.039)*	*(45.583)*	*(14.231)*
	Trend*Landsl.	-0.097***	-0.138	-0.259	1.903	8.974	-20.495
		(0.029)	*(0.149)*	*(0.8)*	*(2.72)*	*(13.544)*	*(27.361)*
	Trend*Wildfire	-0.069**	-0.063	0.141	3.298	20.399	-1.826
		(0.028)	*(0.134)*	*(0.815)*	*(2.606)*	*(14.149)*	*(37.397)*

Table C.3: Robustness analysis for deaths. Quantile regressions estimates for selected quantiles and OLS estimates on deaths. Covariates on first column. Method is modified Barrodale-Roberts algorithm (Koenker and d'Orey, 1987)). Bootstrapped standard errors according to x-y pairwise resampling algorithm, as recommended in Efron and Tibshirani (1994). p-value: *** < 0.01, ** < 0.05, * < 0.10, two-tailed.

	Variable	70th	80th	90th	95th	99th	OLS
(1) 1960-2014	Intercept	52.38***	98.155***	236.245***	488.322***	3663.826***	2135.091***
		(2.978)	(5.398)	(19.704)	(47.681)	(1286.07)	(528.131)
	Trend	-0.933***	-1.734***	-4.207***	-8.619***	-66.677***	-49.854***
		(0.063)	(0.115)	(0.389)	(0.922)	(24.418)	(13.575)
	Population	0.055***	0.088***	0.161***	0.363***	1.015**	0.487
		(0.004)	(0.009)	(0.019)	(0.083)	(0.459)	(0.485)

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Table C.3: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(1) 1970-2014	Intercept	35.591***	68.696***	153.487***	330.848***	1612.991***	787.912***
		(2.007)	(4.408)	(14.159)	(37.153)	(498.961)	(161.823)
	Trend	-0.723***	-1.396***	-3.137***	-6.802***	-31.497**	-19.893***
		(0.054)	(0.118)	(0.359)	(0.875)	(12.607)	(5.314)
	Population	0.054***	0.087***	0.172***	0.384***	1.053***	-0.029
		(0.005)	(0.009)	(0.019)	(0.082)	(0.365)	(0.162)
(1) 1980-2014	Intercept	26.413***	49.447***	111.492***	232***	1092.117***	484.34***
		(1.55)	(3.884)	(8.558)	(25.157)	(236.964)	(122.497)
	Trend	-0.643***	-1.182***	-2.71***	-5.661***	-23.986***	-15.076***
		(0.057)	(0.141)	(0.298)	(0.839)	(8.396)	(5.444)
	Population	0.051***	0.082***	0.165***	0.382***	0.99***	-0.03
		(0.005)	(0.009)	(0.017)	(0.079)	(0.28)	(0.135)
(2) 1960-2014	Intercept	61***	112.889***	292.286***	627.097***	4676***	2128.773***
		(3.283)	(5.108)	(20.247)	(53.876)	(1196.442)	(519.053)
	Trend	-0.938***	-1.778***	-4.786***	-10.323***	-84***	-47.281***
		(0.07)	(0.108)	(0.417)	(1.1)	(23.226)	(13.328)
(2) 1970-2014	Intercept	43.8***	86.545***	203.7***	454.952***	2215.231***	781.06***
		(2.74)	(4.612)	(16.358)	(39.525)	(513.206)	(160.287)
	Trend	-0.72***	-1.545***	-3.7***	-8.476***	-41.615***	-19.873***
		(0.075)	(0.125)	(0.439)	(1.056)	(14.413)	(5.278)
(2) 1980-2014	Intercept	34.957***	68.778***	156***	347.6***	1581.2***	478.866***
		(1.858)	(3.566)	(11.974)	(29.627)	(288.569)	(120.377)
	Trend	-0.652***	-1.444***	-3.294***	-7.6***	-32.8***	-15.116***
		(0.069)	(0.132)	(0.424)	(1.102)	(11.797)	(5.43)
(3) 1960-2014	Intercept	48.989***	92.323***	216.507***	445.295***	3529.95**	2107.043***
		(2.788)	(5.258)	(20.651)	(42.035)	(1396.859)	(529.527)
	Trend	-0.828***	-1.556***	-3.669***	-7.637***	-63.857**	-48.102***
		(0.059)	(0.112)	(0.418)	(0.825)	(26.763)	(13.784)
	Population	0.072***	0.116***	0.226***	0.571***	1.349***	0.702
		(0.004)	(0.01)	(0.042)	(0.12)	(0.453)	(0.566)
	GDP	-0.002***	-0.003***	-0.006***	-0.013***	-0.03***	-0.039
		(0)	(0)	(0.001)	(0.002)	(0.01)	(0.054)

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Table C.3: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(3) 1970-2014	Intercept	34.039***	64.31***	138.686***	296.385***	1505.322***	782.335***
		(1.845)	(3.973)	(11.633)	(28.555)	(411.647)	(162.051)
	Trend	-0.635***	-1.208***	-2.581***	-5.682***	-28.214**	-19.294***
		(0.052)	(0.102)	(0.298)	(0.707)	(11.033)	(5.391)
	Population	0.073***	0.114***	0.221***	0.556***	1.367**	0.036
		(0.005)	(0.009)	(0.043)	(0.122)	(0.582)	(0.19)
	GDP	-0.002***	-0.003***	-0.006***	-0.013***	-0.041***	-0.012
		(0)	(0)	(0.001)	(0.002)	(0.013)	(0.018)
(3) 1980-2014	Intercept	25.891***	47.557***	102.498***	207.265***	953.522***	482.773***
		(1.601)	(3.255)	(7.805)	(21.072)	(225.345)	(122.519)
	Trend	-0.55***	-1.018***	-2.144***	-4.39***	-16.981**	-14.442***
		(0.061)	(0.118)	(0.282)	(0.714)	(8.472)	(5.511)
	Population	0.07***	0.111***	0.208***	0.526***	1.374***	0.031
		(0.006)	(0.008)	(0.034)	(0.121)	(0.41)	(0.158)
	GDP	-0.002***	-0.003***	-0.006***	-0.013***	-0.047***	-0.011
		(0)	(0)	(0.001)	(0.002)	(0.011)	(0.015)
(7) 1960-2014	Intercept	25.646***	43.203***	103.591***	180.611***	475.631***	16.399
		(2.062)	(3.311)	(8.216)	(28.803)	(110.221)	(903.686)
	Trend	-0.495***	-0.82***	-1.91***	-3.283***	-3	-0.393
		(0.041)	(0.067)	(0.161)	(0.575)	(4.337)	(24.017)
	Population	0.046***	0.074***	0.114***	0.261***	0.845***	0.446
		(0.004)	(0.007)	(0.015)	(0.063)	(0.328)	(0.508)
	Low	4.728	50.988***	118.777	344.389*	4809.733	3237.623
		(12.497)	(16.594)	(85.676)	(184.651)	(73488.164)	(2017.464)
	Lower-Mid.	90.509***	186.922***	540.438***	1105.447***	11046.738	5572.378***
		(9.21)	(25.29)	(90.145)	(217.176)	(6793.144)	(1285.534)
	Upper-Mid.	29.164***	40.884***	79.661**	201.94***	289.672	28.335
		(4.467)	(7.888)	(31.357)	(47.228)	(194.628)	(1402.685)
	Trend*Low	0.112	-0.698*	-1.639	-5.405	-93.268	-68.224
		(0.264)	(0.356)	(1.785)	(3.666)	(1360.854)	(50.356)
	Trend*Lower	-1.482***	-3.252***	-9.712***	-20.102***	-210*	-128.976***
		(0.193)	(0.513)	(1.772)	(4.21)	(125.6)	(33.609)
	Trend*Upper	-0.51***	-0.69***	-1.325**	-3.474***	-7.443	-2.414
		(0.093)	(0.161)	(0.639)	(0.941)	(5.815)	(36.093)

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Table C.3: (continued)

	Variable	70th	80th	90th	95th	99th	OLS
(8) 1960-2014	Intercept	80.101***	149.451***	401.514***	933.471***	11144.71***	1426.825*
		(6.247)	(12.774)	(42.966)	(105.911)	(4271.256)	(839.66)
	Trend	-1.394***	-2.63***	-7.256***	-17.014***	-206.299***	-30.512
		(0.13)	(0.262)	(0.857)	(2.039)	(79.407)	(21.565)
	Population	0.055***	0.087***	0.175***	0.374***	1.144***	0.513
		(0.004)	(0.008)	(0.023)	(0.078)	(0.305)	(0.492)
	Arid	-38.969***	-79.89***	-138.61*	-389.277***	-8210.026	9346.071***
		(8.276)	(16.523)	(73.629)	(148.173)	(31740.168)	(1669.464)
	Cold	-35.713***	-67.05***	-187.661***	-590.111***	-10364.268**	-1525.608
		(10.5)	(20.103)	(60.546)	(129.438)	(4323.54)	(2307.859)
	Temperate	-40.802***	-79.623***	-265.381***	-685.907***	-10685.735**	-1050.844
		(6.821)	(14.119)	(44.899)	(110.891)	(4277.44)	(1178.401)
	Polar	0.263	-34.494	-265.987*	-799.994**	-10501.463**	-1421.561
		(39.82)	(53.325)	(157.897)	(318.867)	(4290.646)	(4958.194)
	Trend*Arid	0.741***	1.562***	2.519*	7.471**	152.214	-226.048***
		(0.181)	(0.352)	(1.49)	(2.954)	(588.044)	(42.709)
	Trend*Cold	0.507**	1.025**	3.208***	10.851***	194.138**	34.109
		(0.224)	(0.408)	(1.216)	(2.57)	(80.45)	(58.807)
	Trend*Temper.	0.671***	1.36***	4.843***	12.819***	206.364***	20.621
		(0.141)	(0.29)	(0.898)	(2.186)	(80.025)	(30.324)
	Trend*Polar	-0.054	0.724	5.803*	15.794**	200.942**	27.606
		(0.857)	(1.241)	(3.336)	(6.626)	(79.466)	(127.949)
(9) 1960-2014	Intercept	59.002***	105.054***	233.237***	538.712***	8827.695**	962.74
		(3.9)	(6.895)	(22.447)	(100.582)	(3468.712)	(832.39)
	Trend	-1.12***	-1.983***	-4.345***	-10.01***	-163.608**	-22.718
		(0.078)	(0.135)	(0.431)	(1.929)	(64.985)	(22.18)
	Population	0.045***	0.078***	0.137***	0.311***	1.11***	0.592
		(0.004)	(0.009)	(0.019)	(0.084)	(0.411)	(0.486)
	Drought	-59.065***	-105.066***	-233.153***	-144.089	154790.7	17829.452***
		(3.902)	(6.894)	(28.376)	(395.526)	(456705.437)	(1957.838)
	Extreme T.	64.52***	73.747	107.304	-66.039	-9155.375**	-1174.756
		(24.555)	(81.82)	(129.632)	(518.044)	(3554.244)	(3156.274)
	Flood	-1.45	-0.685	42.666	-7.273	-7149.293**	-786.845
		(7.091)	(10.822)	(35.49)	(109.771)	(3445.519)	(1188.695)
	Landslide	38.546***	42.316*	38.242	-118.362	-6866.275*	-800.36
		(14.53)	(23.581)	(64.018)	(148.401)	(3619.686)	(2228.991)
	Wildfire	-59.293***	-105.618***	-229.842***	-532.089***	-8777.047**	-955.782
		(3.906)	(7.336)	(23.848)	(102.572)	(3468.38)	(3056.532)
	Trend*Drought	1.115***	1.977***	4.34***	2.61	-2866.486	-434.164***
		(0.078)	(0.135)	(0.544)	(7.385)	(8457.98)	(54.143)
	Trend*Extreme	-0.709	-0.083	1.429	10.525	386.68*	33.341
		(0.538)	(1.726)	(3.084)	(11.788)	(198.968)	(74.525)
	Trend*Flood	0.141	0.211	-0.534	0.687	134.081**	17.22
		(0.146)	(0.223)	(0.701)	(2.142)	(64.628)	(30.561)
	Trend*Landsl.	-0.442	-0.481	-0.18	2.795	129.901*	15.674
		(0.319)	(0.511)	(1.386)	(2.968)	(68.075)	(58.758)
	Trend*Wildfire	1.131***	2.036***	4.46***	10.203***	163.31**	20.916
		(0.079)	(0.151)	(0.481)	(2.012)	(65.138)	(80.312)

Appendix D Additional Material

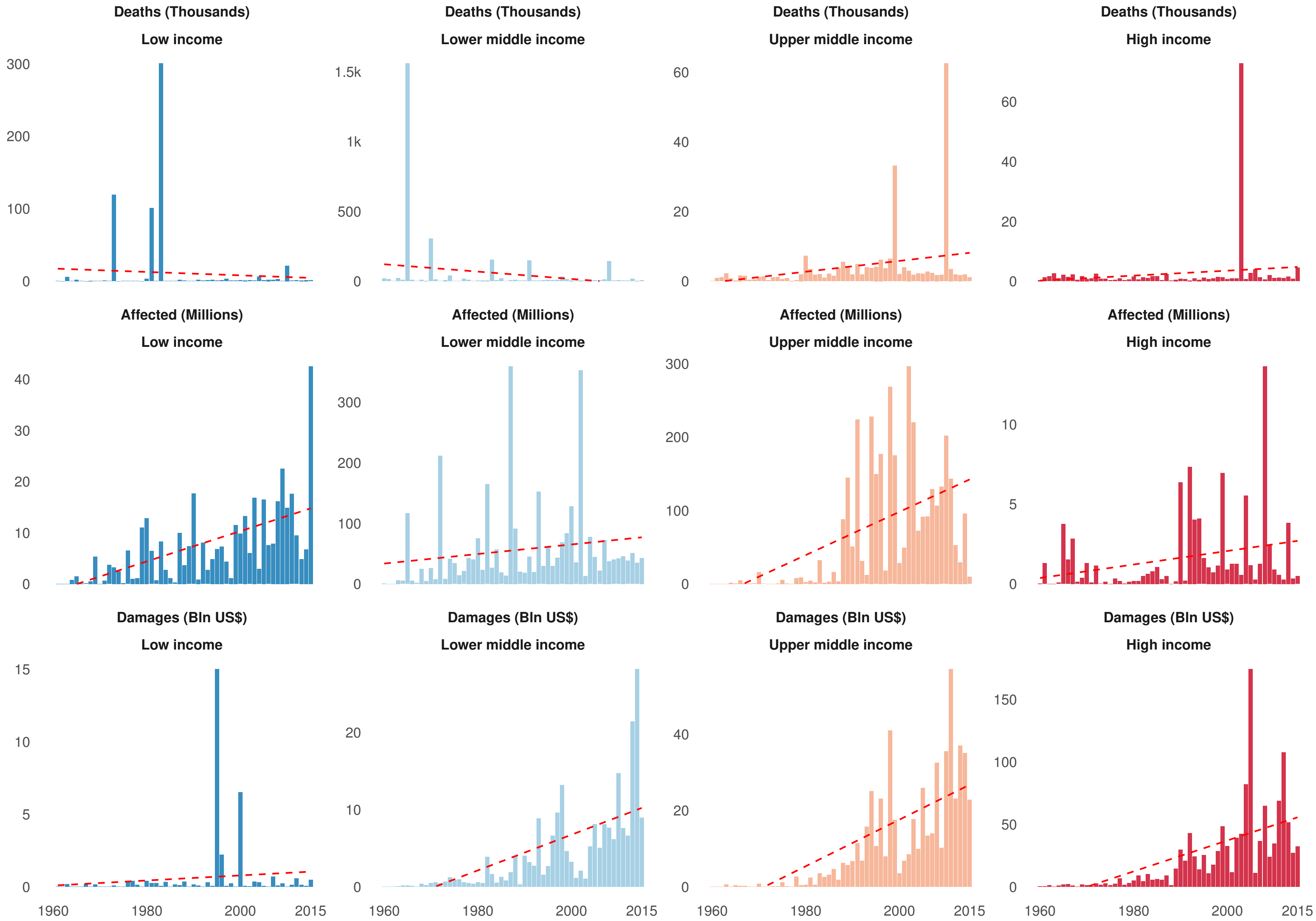

Figure D.1: Yearly sum of losses, by type of loss and income level. Red dashed lines are OLS trend estimates. Time span: 1960-2015.

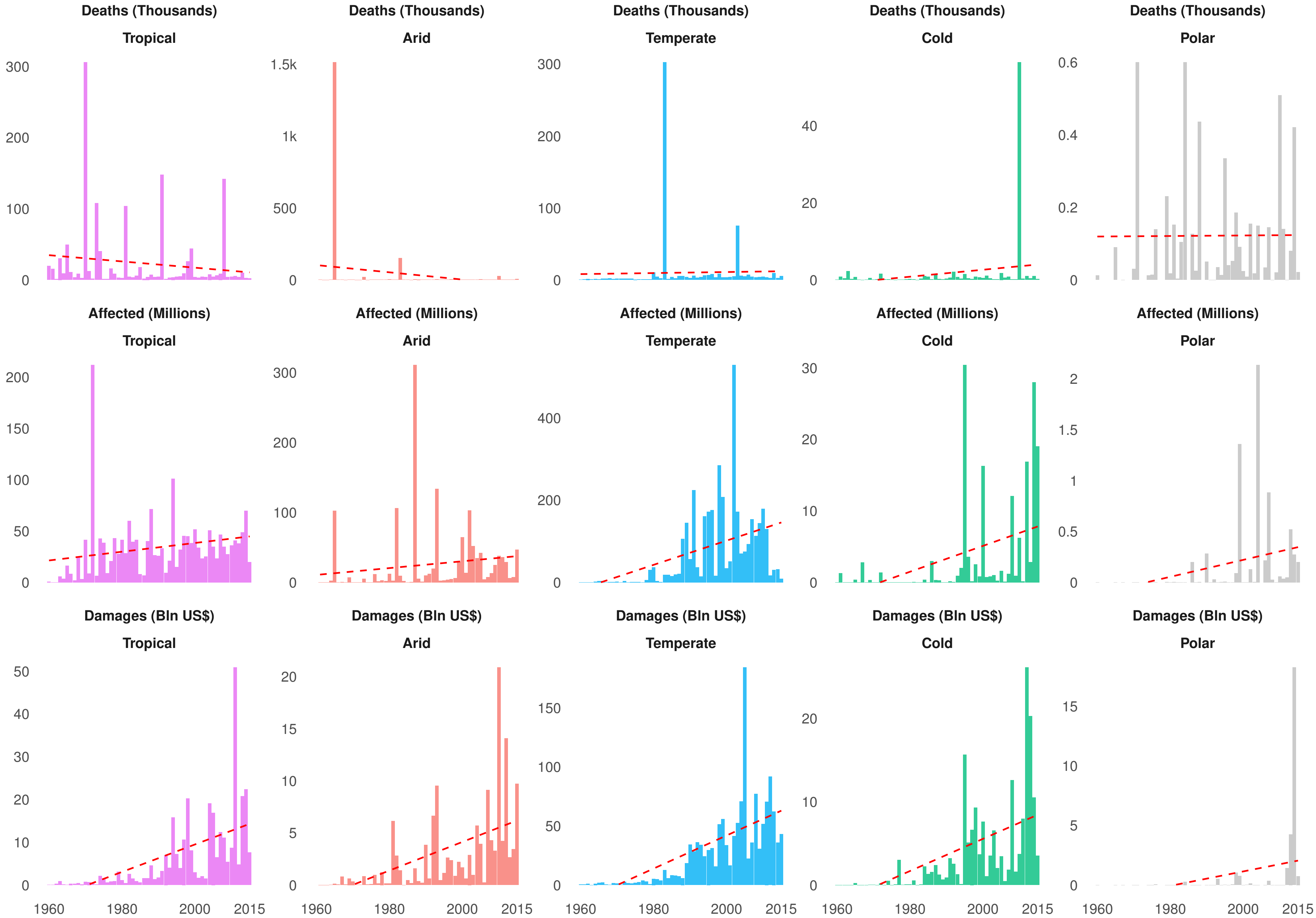

Figure D.2: Yearly sum of losses, by type of loss and Köppen-Geiger climate zone. Red dashed lines are OLS trend estimates. Time span: 1960-2015.

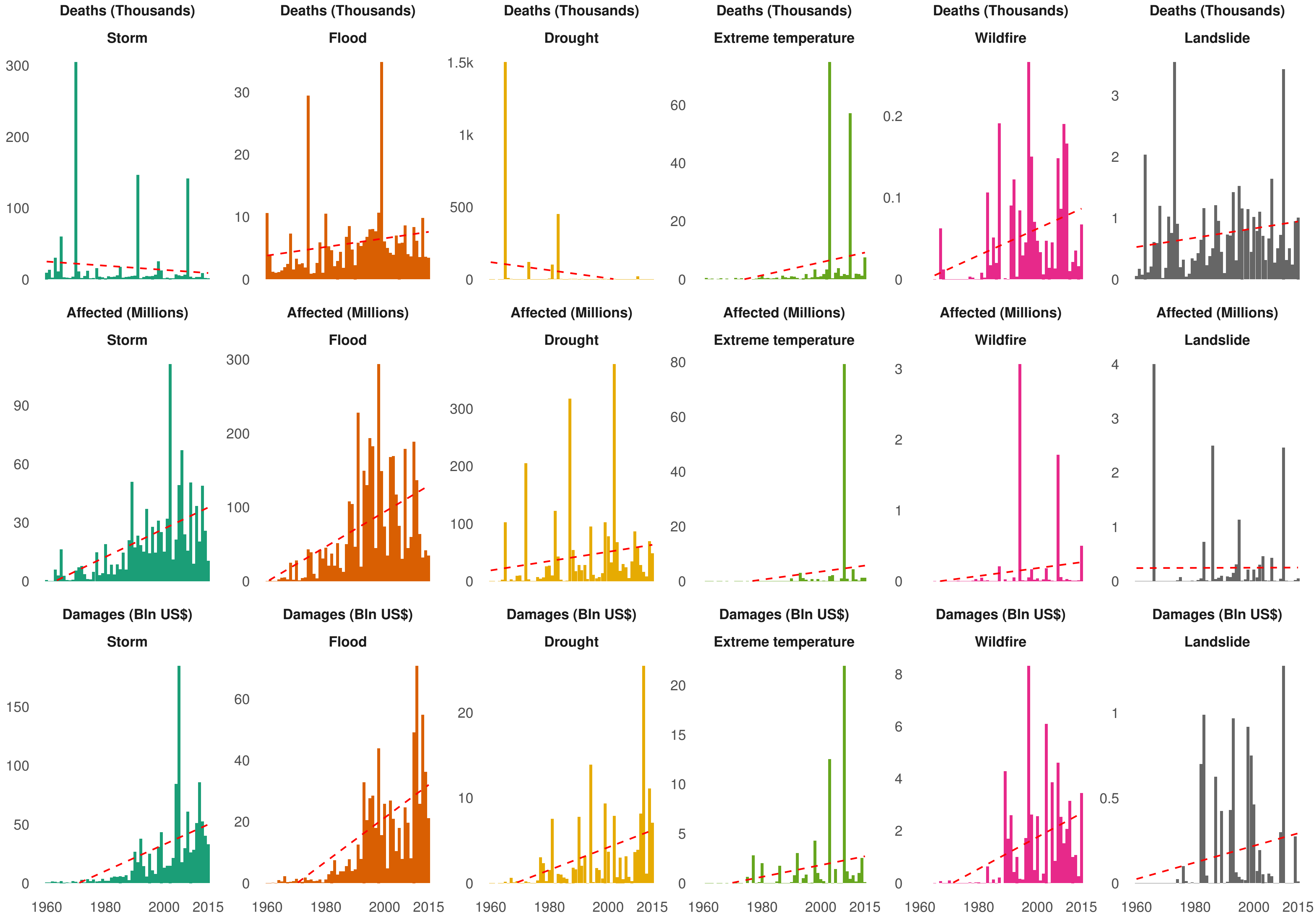

Figure D.3: Yearly sum of losses, by type of loss and disaster type. Red dashed lines are OLS trend estimates. Time span: 1960-2015.

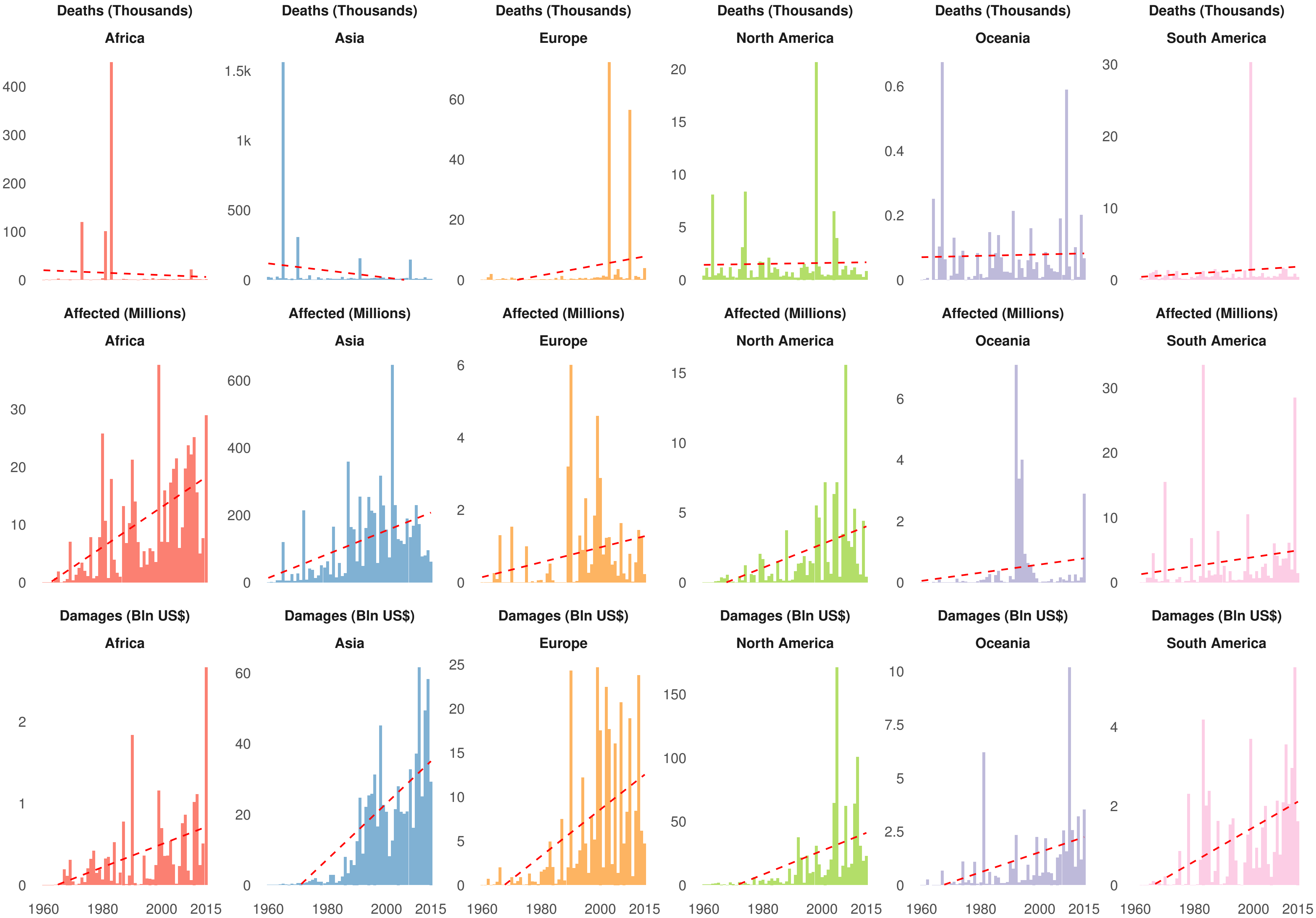

Figure D.4: Yearly sum of losses, by type of loss and continent. Red dashed lines are OLS trend estimates. Time span: 1960-2015.