Analysis of Trends in Disaster Risk

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Abstract

We follow the United Nations Sendai (2015) framework for the reduction of disaster risk to go beyond traditional impact measures and compute the Sendai targets for *individual risk* and *property risk* . We show that individual risk is "very likely" falling between 1970 and 2019 while property risk is "likely" falling between 1980 and 2019 ; additionally, the related *financial* risk, faced by insurers, is increasing over the same period with "virtually certainty". We underscore the greater burden befalling developing economies over the long run , since individual and property risk are respectively 2 and 3 times larger than in the OECD. Singular assessments for Bangladesh, Switzerland and the USA are used to show melioration and convergence but also the limits of our global analysis.

Keywords: Disaster; Natural Hazard; Risk; Trend; Economic Cost; Economic Growth; Developing Countries
JEL codes : Q54; D81; G22; O20

Highlights

- The (global) risk of dying in a natural disaster is "very likely" falling
- Global property losses per unit of wealth are "likely" falling
- Global financial losses per unit of wealth are "certainly" rising
- Financial losses amount to 2‰ of Gross National Income (in the long run)
- Property losses double financial losses
- Individual and property risk in developing countries triple the OECD levels

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1 Introduction

In 2017, hurricanes Harvey, Irma and Maria sowed devastation in quick succession throughout the Caribbean and the southern United States, renewing the interest of western media for these evils which otherwise predominantly strike poor people living in developing countries (cf. Sawada and Takasaki (2017)). The next two years featured powerful typhoons striking East Asia; while overall less devastating, 2018 & 2019 ranked high in historical tables for total losses. As world population keeps increasing and the global economy continues to grow, disasters generated by natural hazards are bound to find more to destroy on their path. Concurrently, our societies are increasingly aware that impacts are not only shaped by climatic events but also by design choices regarding zoning, infrastructures or river management, to name a few. Compounding this complexity is the fact that weather patterns display a long term regularity: stricken zones will, in all likelihood, be hit again in the future. This makes post-disaster decisions crucial drivers of future vulnerability.

For decades now, the UN has spearheaded an international effort to reduce disaster risk. The current Sendai (2015) framework outlines 7 targets and 4 priorities, interconnected with the sustainable development goals (SDGs), to monitor the efforts undertaken by member countries. We contribute to the "understanding of disaster risk" (priority #1) together with a specific computation of individual and property risk (targets A & C). Even tough the concept of **risk** has been an integral part of the UN disaster discourse, most of its communication revolves around dramatic events and some exemplary successes. Beyond this endeavor to raise awareness, the UN also reports **impact** statistics on events, casualties and economic damage whose positive time trend is well known (and confirmed here). Importantly, the UN GAR (2019) report (ch. 8) makes good of the Sendai framework and offers for the first time some point estimates of disaster risk, albeit under a severe data limitation since it is restricted to recent years and a subset of world countries. After carefully defining the risk to life and property generated by natural disasters, as well as the pitfalls inherent in this endeavor, we perform a careful econometric analysis of trend over up to 50 years using information gathered from 4 different sources.

The next section deals with the thorny question of defining a disaster caused by a natural hazard, so as to delineate our field of investigation; it reviews the theoretical literature. The third section then looks at the information sources used to record disasters characteristics and consequences, also pointing to the relevant literature. Section 4 updates until 2019 the impact indicators used by the media and public bodies to communicate on disasters. Section 5 then make the case for using the indicators of *risk to life* and *risk to property*; we study their long-term empirical behavior. We also consider a few polar countries cases from which we draw more precise conclusions while highlighting the need to treat each with care. The important role of climate change is assessed in §6, taking advantage of the concepts and frameworks previously introduced. Section

7 concludes.

2 Nature vs. Society

In this article, *natural disaster* must be understood as a shortcut for a "human disaster caused by a natural hazard",[1] the latter being an extreme event occurring naturally and whose origin may be biological, geological or (most frequently) meteorological. As Quarantelli (1985) recalls, practitioners have long held a disaster easier to recognize than to define. The formalization adopted by UNDRO (1980), and maintained in definition 1.1.2.1 of the IPCC (2012)) report on extreme weather events is thus staunchly centered on physics . O'Keefe et al. (1976) nevertheless challenge it and suggest taking out nature as it is solely a trigger. Indeed, a powerful natural event taking place over an area void of human settlement (e.g., island, forest or mountain) will not make it into disaster databases for two reinforcing reasons: there was no one in harm's way and no one to report the event. A natural disaster thus connects an extreme natural phenomenon and a vulnerable and exposed human group. Furthermore, it is now agreed that the root cause of disasters is the uneven development among and within countries that pushes people into this dangerous situation. Sociologists and psychologists further insist on taking a broader view and factor in the long run consequences for communities stricken by disasters.[2] The recognition of the expanded definition of a disaster is most apparent when looking at the various management stages: *ex-ante* activities include (long-term) prevention, mitigation and (short-term) preparedness. During and after the natural event onslaught, immediate responses feature relief and rescue; afterwards, *ex-post* activities involve recovery and reconstruction (cf. Quarantelli (1997)). Even though wildfire disasters are mostly man-made,[3] we treat them as natural disasters; at any rate, their low frequency makes no discernible impact on our study.

The case of *famines, epidemics and droughts* (so-called FEDs) requires a specific treatment. Indeed, these phenomena feature a strong social component[4] and a very distinct natural development when compared to meteorological disasters; specifically, onslaught is slower, longer lasting and geographically broader. The long lead time to an actual disaster makes intervention and mitigation feasible; hence, not only does the social component play a role in the development

[1] The UN introduced "natural disaster" in 1980 and used it until 2011 when it dropped the adjective to accentuate the human responsibility in disasters, a choice we second IPCC (2012).

[2] Consider for instance estimating the aftermath death toll of hurricane Maria over Puerto Rico in 2017 i.e., how many people who would still be alive if not for the long lasting chaos thus generated (cf. Hammer (2018)).

[3] Humans are responsible for 84% of fires in the US (Balch et al. (2017)) and 96% in Europe (de Rigo et al. (2017)). In malevolence cases such as arson (half of European wildfires), the resulting disaster is man-made, being akin to terrorism rather than an "act of god". When the fire arises from an accident or honest mistake, a disaster ensues only if severe weather conditions concur, making the "natural" classification adequate.

[4] Even for droughts, the distribution (within the population) of the scarce available water is a social outcome.

of the crisis, it can also, through anticipation, play a role in its resolution (or altogether avert it). These characteristics lead Quarantelli (2001) to question the "disaster" labeling of FEDs from a theoretical and operational viewpoint, seeing them instead as social problems, involving chronic natural stress that, when combined with an acute weather event, may lead to a disastrous outcome. Drought-induced famine is then a continuous developmental problem, intimately linked to poverty, corruption and institution building, as shown recently by Irogbe (2013).[5] Next, epidemics such as the Ebola virus in Africa (cf. Coltart et al. (2017)), the opioid abuse crisis in the US (cf. deShazo et al. (2018)) or the AIDS pandemic (cf. Jones et al. (2019)) may have a natural trigger but their development is mostly activated by human exposure and vulnerability.[6] To avoid controversy and enhance the coherency of our work, we shall follow on the footsteps of the commercial disaster databases by solely counting the farm losses from drought, ignoring all other FEDs; the public EM-DAT database is thus filtered accordingly.

3 Information Sources

Reinsurance companies SwissRe, MunichRe and Aon-Benfield maintain extensive private databases of natural disasters. Their regular press releases about disaster impact form the backbone of media reports and part of our own effort; our main source is the open-access EM-DAT database also favored by academia and multilateral institutions.[7] The overall information quality is deemed poor by the OECD (1994) manual , noting that "partial coverage and the lack of internationally agreed definitions and protocols for collecting disaster statistics means that none of the existing databases currently provides a satisfactory basis for the global analysis of the occurrence and impact of the principal disaster types". In response, an effort has been made by MunichRe and EM-DAT (cf. Below et al. (2009)) at developing common rules and methods. Still, the UNISDR (2016) report, dedicated at improving data collection, calls for a cautious interpretation of analytical results, finding that all disaster databases still suffer from endogeneity problems we shall now review.

Firstly, a disaster is assessed only when researchers become aware through the news channels or the insurance industry, a process that biases heavily against older events from an epoch when no one was scrutinizing recurring meteorological events such as floods or storms. Hoeppe (2016), once the research director at MunichRe, explains that their collection contains about 26 catastrophes (aka major disasters) per year for the period 1900-1950. Then, over the period 1951-1980,

[5] World Peace Foundation (2018) reveals that, except for Sudan in 1984, all famine cases in recent decades are war-induced, thus reducing the natural component to a minimum. Even the "risk-of-famine" declared by the UN in 2017 regards countries enduring wars, unrest or civil strife (cf. O'Brien (2017)).

[6] Recent judicial cases in the US show these channels at work for the diffusion of powerful opioids in the population.

[7] This database containing over 10 000 records is operated by the Centre for Research on the Epidemiology of Disasters at UCLouvain, with support from USAID's Office of Foreign Disaster Assistance (OFDA).

their team managed to collect information about most (natural) disasters occurring in western countries, about 100 per year. Finally, starting 1980, minor disasters from all over the world started being assessed and the number of records rose to about 700 per year. This steep increase in the apparent frequency of disasters is thus completely unrelated to the physical laws governing natural hazards. In agreement with chapter 4 of IPCC (2012), the year 1980 is taken to be an adequate starting point for the study of the economic dimensions of disasters.[8] For fatalities, our starting point is 1970 as the major catastrophes making up the yearly tally were already well recorded.

Secondly, global disaster databases are biased against areas with low insurance coverage (e.g., the poorer countryside within a nation) because insurance companies and their field agents are the most reliable source of information relative to disasters. Deficient information transmission also create a bias against events occurring in non-english speaking countries and in developing nations whose local administration and news networks are still weakly developed. To correct somehow for these deficiencies and guarantee a proper assessment of candidate events, stringent selection criteria are applied: EM-DAT requires 10 casualties or 100 affected people or a state of emergency declaration, SwissRe (2017) either 20 casualties, 50 injured, 2000 displaced, 100 M$ of economics losses or 50 M$ of insured losses while Aon Benfield (2019) requires half of these figures; lastly, MunichRe (2018) aims at recording all disasters of natural origin (scaling their severity from 1 to 6), solely discarding those with losses inferior to 3 M$ in rich countries. We thus observe that the set of criteria has either not been changed since their inception or changed to incorporate more events. A mechanical positive selection bias is thus in motion, picking-up more disasters every year as population and income keep rising around the world.

The treatment of insurance is another issue; commercial databases and the US National Oceanic and Atmospheric Administration (NOAA) have in the past acknowledged that **uninsured** losses were simply estimated to be identical to insured ones as if insurance coverage was a uniform 50% across land and time. The damage figure of a natural disaster was thus twice the amount that the local pool of insurers paid to its insured clients in the stricken area. Currently, all databases claim to carefully assess each event in order to estimate properly uninsured losses (without however giving any clues of how this is done). At any rate, the aforementioned practice, which was used for decades, has underestimated the total damages in developing countries where the rate of insurance coverage is much lower than in the US. This is why we separate in a later section the group of (rich) OECD countries from the rest of the world (on the basis of per capita GDP in 1980).

A further point, quite difficult to quantify, let alone test, is exposed by Quarantelli (2001) who notes, based on anonymous interviews, that some authorities have shown an incentive to over-

[8] As reported in Faust et al. (2006), the MunichRe team explains that high quality reports were solely 10% throughout the 1980s, rising during the 1990s to reach 30% in 2005 (cf. figure 1). This selection bias favoring recent years cannot be estimated but certainly makes a rising trend in casualties or damages even more unlikely.

state the human consequences of natural hazards in order to obtain more aid or better international finance deals while other governments tended to understate the impact of natural disasters to mitigate the local political negative reaction (to their unpreparedness).

Looking back at the origin of disaster studies also sheds light on some of the aforementioned biases. Hewitt and Sheehan (1969) appears to be the first effort at recording major (natural) disasters occurring worldwide. Their selection criteria is either 1 M$ of losses (≈ 7 M$ today) or 100 casualties or 100 injured people which means that solely major disasters are recorded. The Anglo-Saxon bias was acknowledged by authors as their sources were the New York Times, Encyclopedia Britannica, Collier's Encyclopedia, American People's Encyclopedia and Keesing's Contemporary Archives. The follow-up by Dworkin (1974) and Thompson (1982) use the exact same sources and selection criteria with an adjustment for inflation. Glickman et al. (1992), on the other hand, expand collection towards man-made disasters and concentrate on loss of life with a minimum threshold of 25 casualties.[9]

At the outset, this section has identified a number of issues regarding the information collection relating to natural disasters. Even though all 4 databases display serious problems, we nevertheless believe them to be useful for a trend analysis. Indeed, inso far as the collection method has not been modified, any selection bias will carry on without altering our risk indicators. Imagine for the sake of the argument that solely 30% of true disasters are recorded in India because the 10 fatalities threshold is too low for some local events to make it to the national level; the situation is thus as if the threshold in India was some larger figure, say 50 victims. Hence, whenever a disaster kills more than 50 people in India, it will in all likelihood be recorded. It is this inter-temporal stability of the criteria that matters when seeking to identify a trend. Note though that this disaster count series is not comparable to an equivalent measure constructed in Belgium because in this smaller country, 10 disaster fatalities will be a catastrophe. Country aggregation must therefore proceed with prudence as we shall do when constructing our two risk indicators.

4 Disaster Impact

Disaster communication emanating from UN bodies (e.g., GAR reports) and the 4 databases (e.g., Below et al. (2020)) invariably revolves around 3 indicators of absolute **impact** over the preceding year, namely *event count*, *casualties* and *damages* (summing estimates of financial and economic losses). They offer a geographic disaggregation by continents as well as a distinction among the main categories of natural events and a comparison with the mean over the previous decade. Unexpectedly, news outlets favor reporting on spectacular and rare natural disasters (e.g., earthquake or volcano eruption) and those occurring on home soil (cf. Eisensee and Strömberg (2007), Yan

[9]The statistical analysis of their database reveals a very good match with EM-DAT which most likely included it.

and Bissell (2018)). Even an encyclopedia entry such as Keiler (2013) fails to escape this sensationalism. Table 1 displays for each database these 3 impact indicators averaged over the last decade (to smooth out year-to-year variations). Valuations are relatively close for casualties but diverge for damages; the public EM-DAT database tends to overemphasize fatalities whereas the commercial databases tend to inflate losses.[10] The reasons explaining such a divergence are impossible to give here since the commercial databases do not divulge their sources, nor their assessment methods. We may nevertheless observe that, being in the insurance business, they gain from showing off the largest possible figures to impress potential clients such as pension funds seeking diversification or the very governments of the countries hit by disasters (who may seek insurance against future events). At any rate, these divergences expound the large uncertainty existing for the estimation of losses; these should therefore be taken with a grain of salt. The large figures featured in Table 1 nevertheless clarify that natural disasters are a serious social problem, killing about 6 people per million population every year and generating extensive economic losses in the regions and countries stricken by natural hazards.

Database	Events	Fatalities	Losses
SwissRe	187	41 638	bn$ 199
AON	319	41 824	bn$ 265
EM-DAT	331	43 244	bn$ 168
MunichRe	689	36 839	bn$ 198

yearly average over 2010-2019

Table 1: Natural Disaster Impact Indicators

To increase our statistical confidence for the inter-temporal analysis of the impact and risk indictors over the period 1970-2019, we average the information gathered from the 4 databases. Due to the strong divergence between MunichRe and the older Swiss-Re and EM-DAT events count, the latter series is solely studied from 1980 on. The evolution of the 3 impact indicators is displayed on Figure 1. Fatalities are challenging to plot as they change by one order of magnitude from one year to the next; we thus display a multiple of the logarithm. A standard econometric analysis reveals the following: per the IPCC terminology (cf. details in §6), it is “virtually certain“ that both *events* and *real losses* (adjusted for inflation) are growing with time (trending-up). On the other hand, the apparent trending down for casualties cannot be confirmed as it is not statistically significant (p-value of 63%). The impactful message send by this simple analysis is well known (cf. Sodhi (2016)) and updated every year in the disasters reports published by all 4 databases as well as by the UN’s global assessment report on disaster risk reduction GAR (2019) (and previous editions).

[10]Note that AON and SwissRe use the US CPI to publish damages expressed real terms whereas EM-DAT and MunichRe use nominal amounts; we apply the US CPI backwards to make all four estimates comparable.

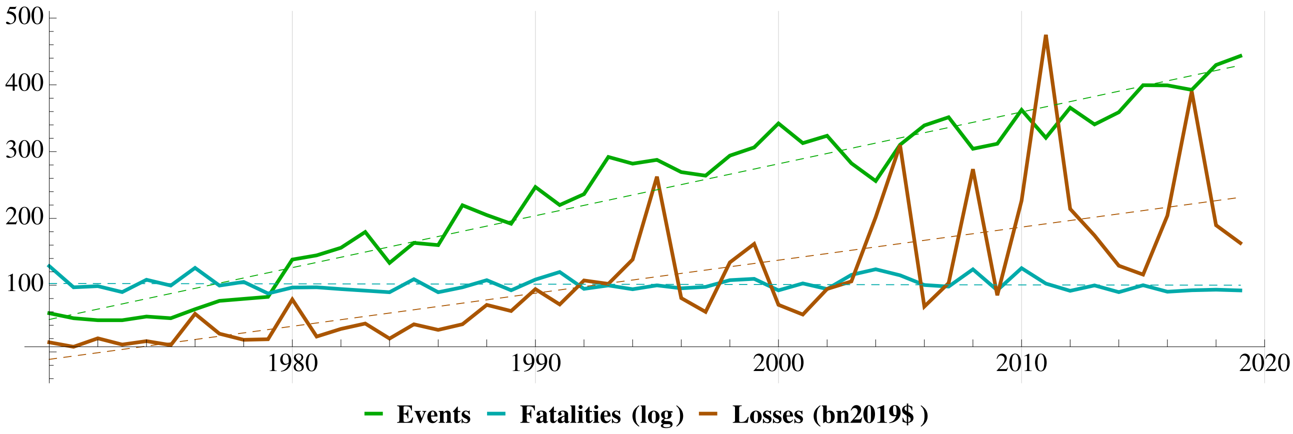

Figure 1: Natural Disaster Impact Indicators

5 Disaster Risk

5.1 Origins

The first assessment of natural disasters, UNDRO (1980), expounds p5 that "risk represents the potential damages and losses, such as the number of lives likely to be lost, the persons injured, damage to property, and disruption to activities caused by a particular natural phenomenon", a view summarized by the formula $Risk = Hazard \times Vulnerability$. At this juncture, impact indicators constitute a first informative step towards measuring the global momentum of natural disasters but, being absolute figures, they ignore socio-economic dimensions such as population growth, urbanization, construction zoning, economic activity (e.g., infrastructure building) and the environment (e.g., river management). Knowledgeable about this shortcoming, UN (1999) introduces *disaster risk* as “the likelihood of loss of life, injury or destruction and damage from a disaster in a given period of time“ together with the updated formula $Risk = Hazard \times Exposure \times Vulnerability$.[11] To better understand the interaction between the natural and human facets of disasters, we shall inquire about the risk they pose to *life* and to *material property*; using these advanced indicators allows one to identity priorities for preventive action (to reduce either exposure or vulnerability).

Risk indicators are briefly touched upon in GAR (2009), if only to emphasize their problematic estimation, given data scarcity, stating (p8) “relative to the size of the global population and GDP, risk may actually be falling”. More recently, GAR (2015) states (ch. 2) “the last decade has seen dramatic reductions in disaster mortality in selected countries” and “in relative terms, the global increase in economic loss from disasters is not statistically significant”; neither statement is detailed with numeric findings. The Sendai (2015) framework is a welcome development that finally

[11]While still excluding terrorism, technological disasters are added to the (now) larger disaster category. SwissRe (2018) distinguishes among man-made and natural origins; the former accounts for about 6% of total damages, a fraction trending down.

brings risk indicators to the forefront by endorsing 7 global targets, 2 of which are our focus here.

5.2 Defining Risk

We define some intuitive risk measures for natural disasters and discuss their utility and relation to the Sendai (2015) framework, highlighting that a crucial one is misconceived.

Frequency ratio of events per billion population

Local individual risk fatalities per million population over a country

Global individual risk average of local risk weighted by population (ζ)

Local property risk ratio of economic losses to gross national income

Global property risk average of local property risk weighted by population (ν)

Global Financial risk ratio of total world losses to world GNI (φ)

The intuitive *frequency* is the least useful indicator because in a densely populated world, a major natural hazard will almost always strike a human community and thus end up counting as a (natural) disaster. Unsurprisingly, neither the absolute event count nor event frequency is studied in the UN GAR reports (cf. Table 2.1 in GAR (2011)).

Individual risk is a statistical measure (not be confused with the terminology used for risk assessment in health or industry) which already appears in Dworkin (1974), Thompson (1982) and Glickman et al. (1992). For country i in year t, we denote $p_{i,t}$ its population and $c_{i,t}$ the casualties from disasters to define the local individual risk as $\zeta_{i,t} = \frac{c_{i,t}}{p_{i,t}}$; this ratio estimates the probability for a random resident to die in a disaster that year. Extending this notion to the entire world requires world population $p_t = \sum_j p_{j,t}$ and the country's share of world population $\sigma_{i,t} = \frac{p_{i,t}}{p_{0,t}}$; we compute $\zeta_t = \sum_i \sigma_{i,t}\zeta_{i,t}$ which is the probability for a randomly picked earthling to die in a natural disaster that year. It will not escape the reader that our indicator simplifies into the ratio of world casualties to world population i.e., $\zeta_t = \frac{c_t}{p_t}$ with $c_t = \sum_j c_{j,t}$. This latter indicator is the **Sendai target A** measuring "mortality relative to population size".[12]

The *property risk* for country i in year t is the ratio $\nu_{i,t} = \frac{L_{i,t}}{W_{i,t}}$ where $L_{i,t}$ denotes the total value of losses and damages from disasters and $W_{i,t}$ the Gross National Income (GNI), with both variables expressed in current USD at market rates (for convenience). This concept captures the gist of **Sendai target C**. Ideally, the replacement cost of assets destroyed by a disaster (e.g., property or infrastructure) should be compared to the existing stock of wealth but since this information is missing for most countries, the property risk proxy is used; it may be rationalized as follows: imagine a disaster strikes a country on New Year's Day generating damages as large as 1% of the local

[12]Target B is the number of affected people over population.

GNI. Since in practice, losses are computed as the replacement cost of damaged assets, it is as if 1% of the workers had to spend their year repairing and rebuilding the damaged infrastructures, machines and appliances. At year end, only 99% of economic activity will have been truly a novel addition of wealth to the country, thereby vindicating the colloquial saying that the disaster costed society 1% of its GNI. Observe lastly that since asset ownership is not equally distributed within the local population, $\nu_{i,t}$ may not be interpreted as an individual measure; rather it is the probability that the local community loses a random asset to a disaster. The *global property risk* may now be defined as the population weighted average $\nu_t = \sum_i \sigma_{i,t}\nu_{i,t}$ which is the probability for a randomly picked earthling that her local community suffers a property loss to a natural disaster.

To the best of our knowledge, the literature (e.g., IPCC (2012) §5.4.2) has always measured the notion of "risk to property" with a related but different concept. Indeed, **Sendai target C**, officially named "direct disaster economic loss in relation to global GDP" is $\varphi_t = \frac{\sum_i L_{i,t}}{\sum_i W_{i,t}}$ which is a *financial risk* because it pools all disaster losses across the world into dollars e.g., from Indian rupees to Danish kroners.[13] Yet, the purchasing power of one dollar of damage vastly differs between these two countries, a fact sorely missed by φ. Consider the following real cases: hurricane Harvey destroyed a staggering 118 bn$ of value on the US gulf coast during 2017; because the USA is also an economic powerhouse, solely 0.6% of its GNI was lost to natural disasters that year.[14] At the other extreme, the 2010 Haiti earthquake wiped a limited 8 bn$ of property but this amounted to 120% of the GNI for this poor country. Financial risk φ computed for this small universe would be 0.6%, the US figure, completely ignoring the vast amount of harm inflicted to Haiti, whereas property risk ν would be above 4%, reflecting the plight of all Haiti's residents. Such a distortion occurs because financial risk is the "GNI weighted" average of the local property risk i.e., $\varphi_t = \sum_i \frac{W_{i,t}}{\sum_j W_{j,t}}\nu_{i,t}$. By focusing on money, *financial risk* deviates from the original Sendai perspective which centers on the human population (suffering the impact of natural disasters). Notwithstanding our criticism of Sendai target C as inadequately defined, we employ it since it features in reports GAR (2009) and GAR (2019).[15]

Starting with Pielke and Landsea (1998) who study hurricane losses in the US, many authors have chosen to normalize losses for property change and/or differences of development. This normalization concept is however criticized by Estrada et al. (2015) for being ad-hoc and unable to distinguish spurious trends from the hypothesized ones, such as the climate change contribution (their criticism also motivates our section §5.4 on stationarity). At any rate, normalization

[13]This ratio is useful for the global reinsurance industry as it tracks changes in their underlying business line i.e., a dollar paid in India for flood insurance is identical to a dollar paid in Denmark for storm insurance.

[14]At the local level, hurricane Harvey wiped about 25% of Houston's GDP (some 100 bn$ out of 400 bn$) while hurricane Maria wiped about 90% of Puerto Rico's GDP.

[15]cf. also the defense of the concept given by Neumayer and Barthel (2011) and the fact that IPCC (2012) §5.4.2 does not even bother defining property risk.

requires high quality information unavailable for most countries, thus impeding its employment for a global analysis.[16] We note finally that recent works on natural disasters like those of Neumayer and Barthel (2011), Loayza et al. (2012) and Visser et al. (2014) rely on datasets ending not later than 2010; the time thus appears ripe for an update, all the more so as the addition of novel data points improves the statistical power of econometric tests.

5.3 Evolution

To compute the individual risk ζ, we use the average of the yearly fatalities count reported by the 4 databases (to improve confidence). Since the construction of the property risk requires individual country information, we solely rely on the EM-DAT database. Our population figures are sourced at the UN while the GNI is sourced from the World Bank and the International Monetary Fund (for the most recent years). Figure 2 displays the evolution of individual risk (fatalities per million people) on a logarithmic scale (gray dots) together with a 5 years moving average (red curve) as well as the trend line (dashed red) . Since risk changes by more than one order of magnitude from year to year, the econometric model estimated with ordinary least squares is $\log(\zeta_t) = \alpha + \beta \text{year}_t$. Per the IPCC terminology, we may say that individual risk is "very likely" trending down with a statistical significance of 6% . Over the more recent 1980-2019 period , the trend parameter is not meaningfully distinct from zero (49% p-value). Hence, the observed downward trend over the longer period appears to be driven by the 1970 Bhola cyclone and the 1976 Tangshan earthquake. The prudent conclusion supported by data is that *Sendai Target A, the risk of dying in a natural disaster, is certainly not growing.* As shown later, a downward trend is identified with almost certainty for some specific countries.

The property risk ratio ν is computed in basis points (100 bp = 1%) and displayed on Figure 3 for the selected 1980-2019 period (gray dots) together with a 5 years moving average (blue curve) as well as the trend line (dashed blue). The econometric model for estimating its growth rate is $\log(\nu_t) = \alpha + \beta \text{year}_t$; per the IPCC terminology, property risk is "likely" falling (p-value of 33%). If we extend the analysis backward to 1970 (with worse data quality), the trend parameter is now positive but not significative at all (p-value of 60%). The average property risk over the last decade is $\nu = 25$ bp which means that for every hundred dollars of wealth generated by (global) economic activity, one ¼$ must be set aside to cover natural disasters losses. This figure looks small at world scale but may be several times over the GNI for a small country (or a region within a large country)

[16] It requires precise knowledge of where economic activity takes place in a country to determine how much GNI is destroyed by a localized natural hazard; this is proxied by population density which is most countries of the world is extremely imprecise. Next, the normalization attributes backwards to a region a share of GNI equal to that existing today. Roughly speaking, if a tornado wiped out a village four scores ago that is now home to the country capital city, the damage is reevaluated a thousand of times greater, a criticizable way of reinterpreting the past.

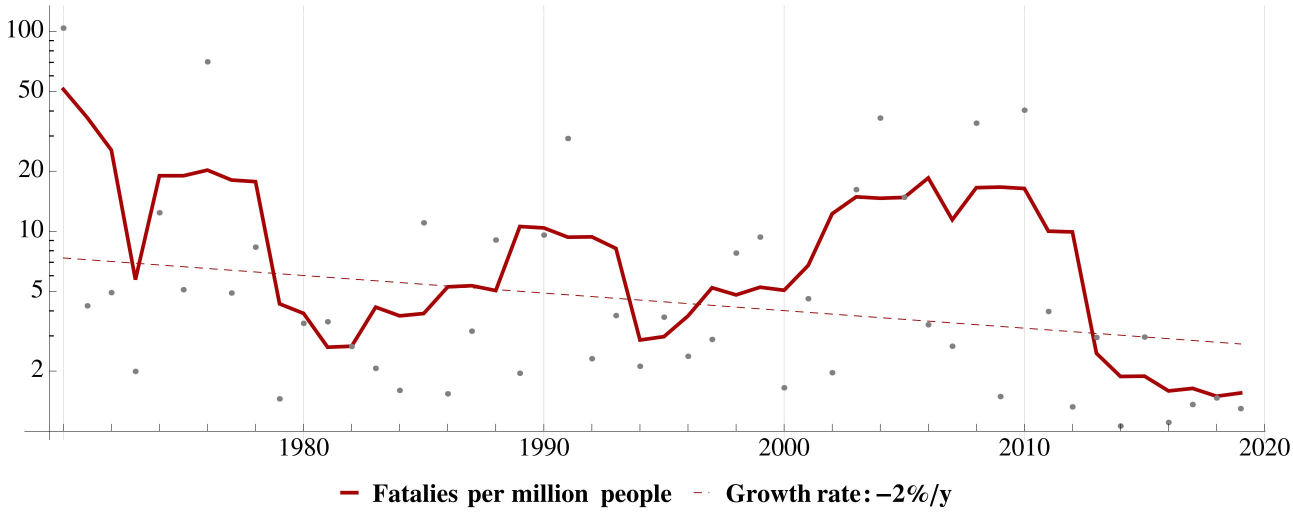

Figure 2: Individual Risk from Natural Disaster

stricken by a major disaster; this is why the mutualization of disaster risk is of paramount importance both within and between countries (cf. Surminski et al. (2016)).

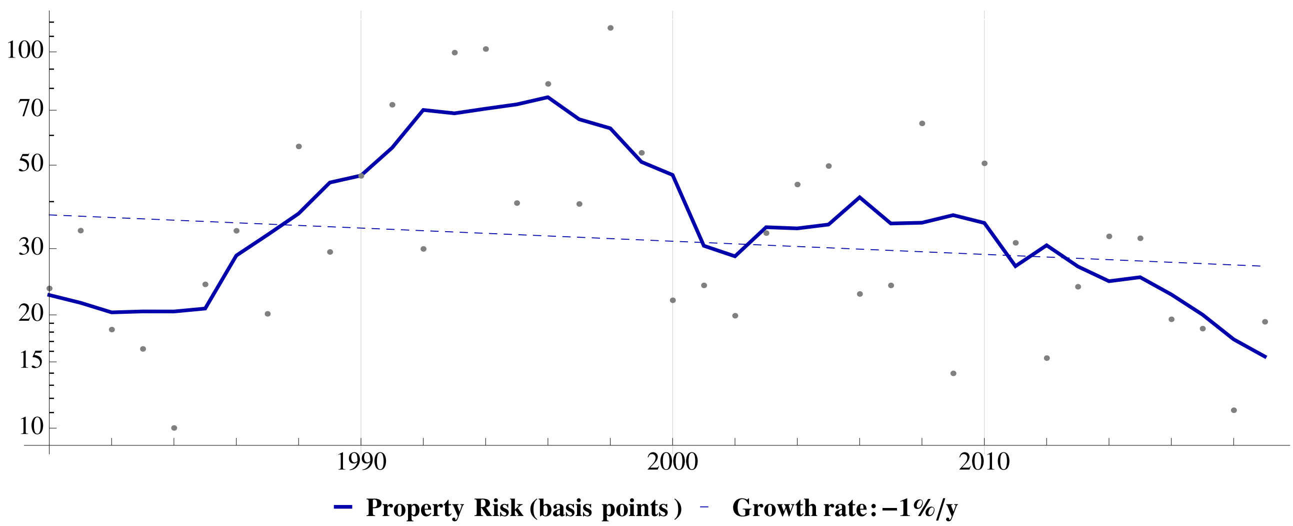

Figure 3: Property Risk from Natural Disaster

For completeness, we display financial risk (aka Sendai target C) φ on Figure 4 . The econometric analysis reveals it to " very likely" trending up (p-value of 2%), driven by the losses originating in the USA as explained in §A.3. The long term average for financial risk is $\varphi = 13$ bp vs. $\nu = 38$ bp for property risk. This empirical finding means that, over the last 4 decades, natural disasters have hit thrice harder the developing countries because natural hazards destroyed a greater share of local assets. In all likelihood, this is due to the fact that these countries lacked the defensive infrastructures put in place by advanced economies.[17] We have thus extended in a precise man-

[17]Our interpretation is buttressed by the GAR (2013) claim that reserving 1‰ of future infrastructure investment for disaster-risk-reduction would generate a very large reduction of future losses to natural disasters.

ner, a result well known for individual risk regarding the inequitable burden distribution of natural disasters across the world. We further observe convergence since the discrepancy between φ and ν over the last decade is reversed with $\varphi = 27$ bp vs. $\nu = 25$ bp i.e., (formerly) developing countries are now better prepared while advanced economies seem to have let their preparedness efforts lapse, suffering now more than in the past (cf. USA §A.3).

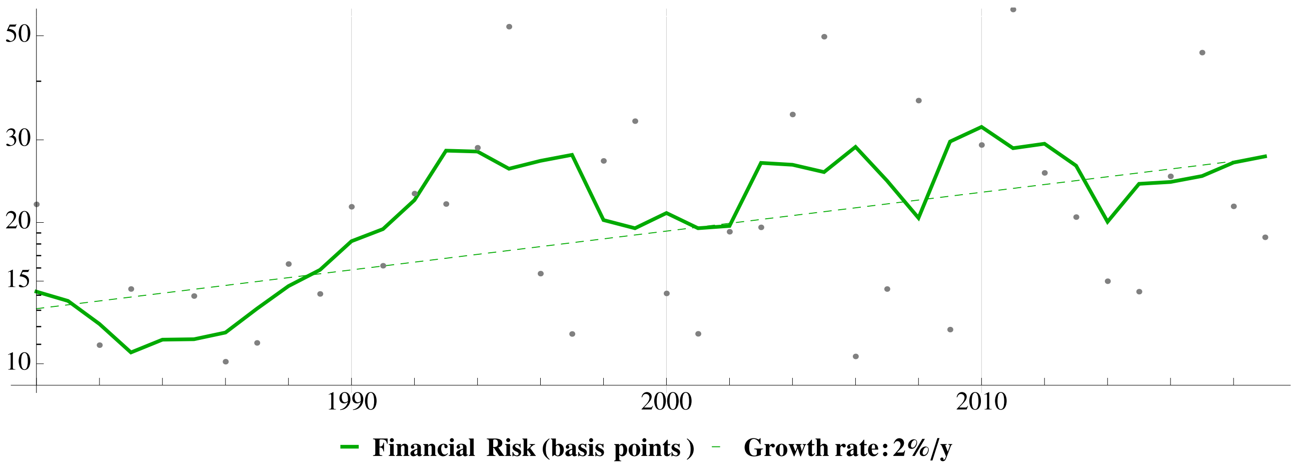

Figure 4: Financial Risk from Natural Disaster

5.4 Stationarity and Unit Roots

When the mean and/or variance of a time series changes over time, it is said to be *non-stationary*. If so, many traditional results of statistical theory cease to apply, calling for special care. A well known example from econometrics textbooks is the *US real quarterly GDP* over which there is still an ongoing controversy in macroeconomics as to whether shocks are transitory or permanent (cf. Kim and Choi (2017)). In econometrics terms, the first case corresponds to *trend stationarity* (TS) whence the series oscillate around a deterministic time trend whereas the second case is called *difference stationarity* (DS) whence the series resembles a random walk. Since several of our variables relate to GDP, we need to test them for stationarity and if the answer is positive, find out an adequate decomposition, either TS or DS.

Our replicable econometric code is available at rpubs.com/nboccard/NDrisk (a full copy is included in appendix). We study the 1970-2019 period; all monetary variables are corrected for inflation with the US CPI and transformed into logarithm as is customary for such an econometric analysis. We find that the logarithm of world yearly real GNI is DS which means that the real GNI growth rate is stationary (i.e., a random walk around 3%). Next, the logarithm of real disaster losses is found to be TS, meaning that disaster shocks are transitory; furthermore, this series has no break in its positive trend. *Individual risk* is found to be DS with a strong mean reversion property: in a given year, risk is likely to be opposed to what happened in the 5 previous ones. In other words, if the past was calm, prepare for the worst and conversely, if a recent year was dramatic, the current one is expected to be milder. A possible break is identified in 1977 setting apart the deadly catastrophes of the early 1970s from the modern (safer) epoch. *Property risk* is also found to be DS with an optimal autoregressive model displaying mean-reversion over 4 years. Our analysis also suggests that structural breaks took place in 1990 and 1999 with the in-between period characterized by a much higher risk. Lastly, financial risk is found to be TS similarly to the absolute real losses and does not feature any break in its positive trend.

5.5 Geography & Development

From a climate change point of view, it makes no sense to distinguish countries since nature ignores borders, but once we broach on the disaster problem from a private property or public safety angle, the distinction becomes relevant since each country has a different level of development, a specific disaster culture and an idiosyncratic set of prevention policies. We have also previously noted how trend identifications was reliant on a few exceptional events or atypical countries. The appendix explores 3 cases, each of which, highlights the fragility of the conclusions reached in the previous section.

Our first country example, Switzerland, hardly ever appears in the disaster databases because of a safe geography and a strong protection culture (as well as the mean to implement it). Yet, extreme weather events still strike it, generating noted economic damages at county level. This demonstrates that not all disasters make their way into the major databases and ultimately means that the extent of damage caused by natural disasters is still underestimated. Switzerland also offers a ray of hope; as we show in §A.1 individual risk is virtually nil but more importantly, property risk has been brought down from already a very low level (compared to world mean) i.e., there's always room for improvement when it come to reduce disaster risk.

Next, without the 1970 Bhola cyclone (and the 1976 Tangshan earthquake), the natural disaster risk-to-life (Sendai target A) would not be trending down. By extension, if an exceptionally deadly event were to take place in the near future, our statistical identification would be weakened (i.e. larger p-value for the trend estimate). At the same time, the study of Bangladesh in §A.2 reveals the success of the UN spearheaded disaster reduction actions: this most suffering country has managed to bring individual risk down to the level enjoyed by intrinsically safer nations (since the Bay of Bengal is a hotspot for typhoons).

Our third example are the USA which we show in §A.3 to be a statistical outlier because of greater insurance penetration. This finding thus means that damage assessment in the rest of the world may have been underestimated since insurance rates are much lower. One way around this exceptionalism is to exclude the USA from the analysis; doing so, property risk would trend down with greater certainty (p-value 26%) and financial risk (Sendai target C) would appear without trend. We also contribute to the debate on whether property risk is rising in the US. The storm component certainly is but the flood one is falling so that the overall risk appears without trend.

The main message of this section relates to the dichotomy between developing and developed nations (on average over the last 4 decades). We previously explained how insurance penetration is used to infer disaster losses; this feature clearly separates nations along the development ladder since insurance coverage is closely related to the overall wealth level of a country. We select the 1980-2019 period where data coverage of natural disasters occurring in the developing world is deemed to be adequate; we associate the "developed" label with the members of the *Organisation for Economic Co-operation and Development* (OECD), for lack of a better discriminating criteria, pulling all remaining countries into the "developing" category.[18]

For each of our three risk ratios, Table 2 displays the long run average, the slope parameter and the probability that it is non zero (p-value). Using the IPCC terminology, we may say that the individual risk ζ is without trend in both regions. Over the long run, disasters of natural origin claimed 8 people per million population in the developing nations, twice more than in the OECD. Over recent decades, comparing the 1990s and the 2010s, the world individual risk fell from 7.2 down to 5.6 (casualties per million population), falling from 8.8 to 6.5 in the developing nations but rising from 1.5 to 3.4 in the OECD, this due to the 2011 Tōhoku earthquake in Japan; this shows once more how infrequent major events perturb statistics, making trend identification difficult.

Property risk ν, measured in basis points, is over the long run thrice larger in the developing world when compared to the OECD (44 vs. 16 bp). The situation appears to improve in the developing world and worsen in the OECD but the regression coefficient are not statistically different from zero. Finally, financial risk (Sendai target C) is about twice larger in the developing world (34 bp) than in the OECD (17 bp) over the long run; trends are very likely, falling in the developing world and rising in the OECD (significative at 5% and 8%).

Indicator	Individual Risk			Property Risk			Financial Risk		
Region	ζ	slope	Prob	φ	slope	Prob	ν	slope	Prob
Developing	8.111	0.054	0.748	43.996	-0.585	0.178	33.963	-0.553	0.055
OECD	3.940	0.085	0.629	16.350	0.256	0.172	16.857	0.370	0.082
World	7.492	0.062	0.671	39.631	-0.432	0.236	20.176	0.173	0.285

Table 2: Econometric analysis developed vs. developing

One theoretical contribution of this article to the better understanding of disaster risk is that the current **Sendai target C** (aka financial risk φ), is solely twice larger in the developing world (compared to the developed one) when in fact, the disaster burden of developing nations, ade-

[18] In doing so, we only drop 300 records out of 4300 with positive damages in the EM-DAT database. Our dichotomy is crude but at the start of the period in 1980, a large wealth gap separated the OECD from the rest of the world.

quately measured with property risk v, is thrice larger. This systematic under-estimation calls for updating Sendai target C with a definition that properly monetize disaster destruction against the cost of rebuilding.

6 Climate Change

The radiative forcing operated by climate change upon the many characteristics of natural hazards has generated a rich literature and some controversy. Let us first to recall how the IPCC method proceeds. As explained by Mastrandrea et al. (2011), a team of specialist authors *reviews* the literature on a specialized topic. If they agree on having gathered enough *evidence*, they proceed to evaluate *confidence* with basic levels low, medium & high. If the quality of this evidence is high enough (per the team subjective opinion), a *probabilistic assessment* is performed with thresholds labeled *virtually certain* for 1%, *very likely* for 10% and *likely* for 33%.[19] Note finally that when the IPCC refers solely to a *confidence* label, it is because the underlying evidence fails to reach the quality threshold needed to perform a probabilistic assessment.

The path-breaking Stern (2007) review concludes that (natural) disaster losses are increasing faster than might be explained by changes in wealth, population, and inflation, thus pointing to a climate change influence. Pielke (2007), among others responses, disputes this claim for its reliance on mere assumptions instead of actual disaster data. Later, the authoritative IPCC (2012) report on *climate extremes and disasters* (SREX) identifies a possible climate change impact but concludes that rising population and increased capital at risk are the key drivers behind the observed increase in (natural) disaster losses. Regarding natural hazards (not disasters), the policymaker summary p8-9 reports “observed long-term increases in tropical cyclone activity (low confidence)”, “observed trends in tornadoes and hail (low confidence)”, “climate-driven observed changes in the magnitude and frequency of floods at regional scales (medium confidence) and sign of these changes at global scale (low confidence)”, “increase in extreme coastal high water related to increases in mean sea level (likely)”, “attribution of any detectable changes in tropical cyclone activity to anthropogenic influences (low confidence)” and lastly that “attribution of single extreme events to anthropogenic climate change is challenging”. Note also that geophysical events such as earthquakes or volcano eruptions are deemed unaffected by climate change.

The physics focused progress report NAP (2016) finds more climate signals as it identifies (p. 31) anthropogenic influence with confidence for extreme temperature events, some confidence for drought and heavy rainfall but little or none for storms and cyclones. In its latest iteration, IPCC (2018) reports medium confidence on the future increase in frequency and severity of natural hazards during this century. Chapter 3 on “Climate Change and Associated Hazards”, referring to the

[19] The threshold enforced by journal editors in the social sciences to consider a result as “statistically proven” is 1%.

past, p201, states “flood frequency and extreme streamflow have increased in some regions (high confidence)”. About the future, it states p203 “expansion of the global land area with significant increases in runoff (medium confidence) and increase in flood hazard in some regions (medium confidence)”, p203 “low confidence regarding changes in global tropical cyclone numbers under global warming over the last four decades”, p204 “limited evidence that the global number of tropical cyclones will be lower under 2°C compared to 1.5°C of global warming, but with an increase in the number of very intense cyclones (low confidence)”. Lastly, WMO (2019) says p29 that “determining the causal factors, including anthropogenic forcings, that contributed to or influenced the probability of extreme events is an area of ongoing research”.

Clearly, all findings point to a negative impact of climate change upon frequency and strength of natural hazards. At the same time, the prudence expressed in the previously cited conclusions reflects the paucity of available natural hazard information, when compared to the well known case of temperature for which daily records over hundred of years and thousands of locations exist. Recall indeed that a weather event can be labeled *extreme* only when some measurable intensity characteristic is above the 90^{th} percentile of the empirical distribution (cf. IPCC glossary). Confident estimation thus requires collecting numerous reliable pieces of information and since low intensity events were not recorded in the past (for lack of interesting features), this task is still ongoing.

North Atlantic hurricanes, for instance, have been studied by NOAA for decades. While landfall over the US continental shelf has been reasonably observed since 1851, global hurricane information has been gathered from the books of ships crossing the ocean which had an obviously limited ability to measure wind speed and correctly classify depressions. Adjustments have been performed by Vecchi and Knutson (2011) up to 1966 when trustable satellite observations became available. From these adjusted data, one can easily check that hurricanes are likely (statistically speaking) becoming more frequent since 1900; should this raw estimation be confirmed, the mean number of *yearly* hurricanes would grow from 6 to 7 over a century. Next, these authors found that the yearly number of hurricanes making landfall over the US (and frequently causing a disaster) varies twice as much but lacks a trend (statistically speaking); there is currently about one in five hurricanes making landfall. The long run behavior of the ratio (of the previous two measures) reveals with virtual certainty that the *hurricane landfall probability* is trending down (−1% per decade) which was already noted by Vecchi and Knutson (2011) in their table 1. As shown by Kossin et al. (2014), this is due to a poleward migration of the location of tropical cyclone maximum intensity. Climate change thus acts in complex fashion upon the risk that a North Atlantic tropical storm hits human settlements in North America: it is likely creating more hurricanes but at the same time changing their trajectories so that the overall risk is falling. The rise in hurricane economic losses over the US is thus entirely anthropogenic i.e., due to people’s increasing tendency to put more assets at risk.

From this particular case, we may derive useful considerations for tackling natural disaster risk. As shown in Table 1 of §4, there's about one natural disaster per day on earth. Thus, if we allow ourselves to extrapolate the hurricane impact frequency to all EWEs, this would mean that about 5 natural hazards take place everyday on earth.[20] What a precautionary scenario for climate change might predict, in that context, is that instead of an average $5 \times 365 = 1\,825$ yearly EWEs, there could be some 10% more, about 2 000 yearly EWEs, at the end of the century; furthermore, some of these additional events would have an anthropogenic origin.[21] Yet, how many of these EWEs will trigger a disaster is quite uncertain since this greatly depends on social preparedness (or its lack thereof). The disaster risk faced by humanity today (and for the coming decades) remain the same, namely dying in a disaster of natural origin (or losing one's property). In other words, natural hazards are a *feature* of the current climate, not of its *evolution* (at least from the point of view of generations alive today). Independently of the direction and speed at which climate is changing, natural disasters will keep striking year after year unprepared communities. It is our contention that anticipating and *adapting* to this fate is the most pressing priority, unless we are willing to sacrifice thousands of actual lives for the well being of our yet unborn offsprings.

The socioeconomic value of acting today on *adaptation* may be illustrated by Hoeppe (2016)'s mention of the Hamburg dikes defenses against storm surges. von Storch et al. (2015) recall that the north sea level has risen at about 2 mm per year over last century and could be rising faster at 3 mm during the current century (as a consequence of climate change). Mean water level in Hamburg will thus possibly rise by 30 cm over the next century, a noticeable rise which should definitely be accounted for. Now, a storm surge occurs when the sea water suddenly rises by at least 3.6 m; such an EWE occurred 6 times since 1750 at levels above 5 m, before the 1962 catastrophe which was exceptional as the level rose to 5.7 m. The massive 3.4 bn€ (2018 real term) damage sustained by the region was met with an even larger 4.7 bn€ investment to raise dikes at about 8 m. Since 1962, five greater floods broke the 5.9 m threshold in 1976, 1994, 1995, 1999 and 2013; luckily they caused almost no damages.[22] The avoided losses are estimated by MunichRe (2012) to be 10 times as large as the original investment. Regional authorities thus proved able to beat climate change to the clock by adapting preemptively.

As the primary duty of the Hamburg port authorities is to protect livelihood and property (and only then to foster commerce), they are already preparing for rare but still recurring storm surges, one of which might possibly go higher than the current 6.5 m known record. Insofar as the "pure

[20] For this educational example we ignore geophysical natural hazards.

[21] Our illustrative 10% increase is commensurate with §3.5 of GAR (2015) on the "additionality of climate change"; it also lies in the possible range found by Forzieri et al. (2016) in a similar prospective study for Europe.

[22] Part of the rise in storm surges absolute levels is due to the very presence of the defensive works along the Elbe river which modifies water circulation.

rate of social time preference" of the German nation is positive (even if very small), it is optimal to spread effort against climate change on both *adaptation* and *mitigation* (cf. Barro (2015)) which, translated into clear objectives, might be city protection and energy transition towards renewables. Because climate change is a public good, it is more efficient to organize the latter task at the federal level (but ideally at the UN level) and delegate the former one to regions and cities. Success stories like Hamburg deserve a greater media coverage as they demonstrate the social value of investing into preparation against future disasters of unknown characteristics.

7 Conclusion

Our study employs the sparse publicly available data on the consequences of natural disasters to confirm and amplify known stylized facts. We recall the difficulties inherent in delineating the very concept of natural disaster as well as the paucity of trustable sources of information. Statistics generated out of these should therefore be taken with a grain of salt. We further argue, in line with UN recommendations, for a focus on *risk ratios* to address developmental objectives.

Our first practical task is to update trend computations for the classical impact indicators of natural disasters. We then show more interestingly that over the long run, the risk of dying in a disaster for a random earth inhabitant (Sendai target A) is "very likely" falling . Next, the risk for a local community to suffer a property loss to a natural disaster is "likely" falling; further analysis indicates a period of rising risk followed by falling risk since the 1990s. On the contrary, the misleading Sendai target C, financial risk, is "very likely" trending up. Over the long run, financial losses have consumed about 2‰ of the world's GNI while property losses have been thrice as large because *poor countries suffer about thrice more destruction for a similar natural hazard*. It is precisely for this omission that financial risk is an inadequate measure for the human focus of the Sendai perspective; it should therefore be replaced by the property risk. Summarizing these empirical findings, we infer that the sustained UN effort at raising attention towards natural disasters has been fruitful since both types of risk appear to have fallen over the last 4 decades.

Next, we analyze three countries to illustrate the existing heterogeneity between nations, and ultimately the need to handle global statistics with great care. The USA is overrepresented in disaster databases but this also allows for an analysis over the very long run. Individual risk is found to be certainly falling. Regarding property, flood risk is trending down while the storm risk is rising; interestingly, the sum of these two major risks fails to display a trend. We look next at Switzerland which enjoys low risk levels but has nevertheless managed to improve further the protection of its residents. We last expound the case of Bangladesh, a country subject to recurrent cyclonic activity without much defense resources. Having been victim of devastating catastrophes, it has managed to prepare better and succeeded in driving down individual risk to an acceptable level, closing in on the world average. Lastly, to account for the striking difference between insurance penetration, we divide the world into developed and developing nations over the 1980-2019 period; we find that individual risk is about twice larger in the developing world compared to the developed one; property risk is even more contrasted being thrice greater. We have thus revealed with precise figures the discriminatory burden of natural disasters.

Regarding policy implications, we have recalled how a socially desirable climate change strategy involves both *adaptation* and *mitigation*. Specifically, we stress that natural hazards are a permanent feature of the climate that threatens human life, which makes a strong case for adaptation. The extensive use by the media of singular events to raise climate change awareness is however tilting the balance away. Indeed, stating a causal link from climate change to a particular disaster leads one to believe that hazards will be avoidable in the future only by dedicating all current and future effort at mitigation. However, opinion surveys show that people concerned by climate change care for the wellbeing of both current and future inhabitants of our planet; they would therefore seek a fair balance between adaptation and mitigation. Since the former delivers its greatest returns where exposure and vulnerability are highest and we have also shown that these conditions are prevalent in the less developed countries (or regions). It then stands to reason that public policies directed at climate change adaptation may also reduce economic inequality.

We partake with the disaster literature that developing countries ought to devote more efforts and investment to counter the increasing financial losses of natural disasters because the socioeconomic returns are large, as the Hamburg "poster case" highlights. Now, this is easier said than done because the immediate burden befalls the public sphere whereas the future benefit of avoided disaster losses reverts entirely to the private sector. The solution undertaken with success by many European countries is firstly to draw a disaster risk map and enforce the corresponding zoning (even if this is politically costly for the government). Next, as detailed in Boccard (2018), the home insurance market must grow to the point of covering all households so as to finance (in a fully socialized way) a disaster fund with an extra percentage fee atop the yearly premium. The fund should be primarily used to build defenses and reduce vulnerability although it will inevitably be used to compensate disaster victims. Once this is basic layer of mutualization is achieved, the third wave seeks to introduce risk sharing with local actors using mandatory disaster insurance at market rates so as to discourage urban development in risky areas.

A Appendix

A.1 Switzerland

The most common extreme weather events (EWEs) taking place in Switzerland are flood and landslides; thanks to its protective mountain range, central location within western Europe and legendary attention to details, the last natural disaster recorded in the EM-DAT database goes back to almost two decades. One therefore studies localized EWEs which the UN refers to as “extensive disasters” (though from the point of view of victims, each is still truly a disaster). Our data covering 1946 to 2018 is sourced at the Federal Statistical Office (BFS) and the Institute for Forest, Snow and Landscape Research (WSL). Both risks measures present a “virtually certain” downward trend vindicated by the estimation reported in Table 3.

Trend	slope	st dev	t-Stat.	P-Value
Individual risk	-0.013	0.004	12.13	0.0011
Property risk	-0.321	0.082	15.42	0.0003

Table 3: Econometric Estimation of risk for Switzerland

The very fact that Switzerland already offered a high level of protection to its citizens 50 years ago, means that the “low hanging fruit” had already been picked-up. From that point on, any further risk reduction was going to be arduous and costly to implement. Yet, the continuing safety increase demonstrates that citizens demanded such a service and that their government was able to deliver it at an acceptable cost. As shown in Boccard (2018)’s detailed study of extensive disasters over neighboring France, property risk has been falling over the last 4 decades, driven by a series of legislative acts, each enacted in response to a disaster that exposed weaknesses in the national protection framework.

A.2 Bangladesh

Bangladesh stands as the polar opposite of Switzerland, being a still developing country that frequently faces the most extreme weather events on its Bay of Bengal coastline, while possessing few means of defense. Our trend analysis shall nevertheless show a similar downward pattern for risk although it starts from a considerably worse situation. Like the USA, but for a distinct reason, Bangladesh is an outlier within disaster databases because it suffered two of the worst historical catastrophes. Their devastating impact distort world statistics and trends. The political context of these tragedies is worth recalling. As explained by Hossain (2018), the 1970 Bhola cyclone took out more than a quarter million lives in “East Pakistan“; this cataclysm triggered the emancipation movement that ultimately lead to the creation of Bangladesh in 1971. It was also in response to

Bhola that the government established, with external financial and technical support, early warning systems and the so-called cyclone preparedness programs (e.g., building concrete shelters).

The second dramatic event that shattered the country was cyclone Gorky which was even stronger than Bhola; it stroked Bangladesh in 1991 causing an estimated 140 000 fatalities. Although this was still a major catastrophe with a death toll as high as 1.3‰ of the population, it was nevertheless three times less severe than Bhola whose population toll ascended to 4.5‰. Closer to us, Paul (2009) explains how many lives were saved upon the passage of cyclone Sidr in 2007, thanks to the successful application of early warning, mobilization and evacuation plans which had markedly improved after the 1991 cyclone (e.g., shelters increased from 500 to 4 000).[23] The death toll fell to a low and exact figure of 3 406 casualties, reflecting improvements in safety as well as administrative record keeping (an indicator of good governance). In 2019, cyclone Fani, the strongest in a decade and of similar energy as Sidr, "solely" killed 89 people in the Bay of Bengal (across Bangladesh and India).

The aforementioned catastrophic casualty figures for 1970 and 1991 are so large that they literally drive the trends. Because the risk fall involves several orders of magnitudes, we estimate $\log(\varphi) = \alpha + \beta year_t$. As shown in Table 4, the individual disaster risk in Bangladesh has been falling with "virtual certainty" at the yearly rate of 7%, as may be observed on Figure 5. Over the last decade, the individual risk is on average about one casualty per million population. Even though, this is still twice more than the Swiss risk, a quick convergence has taken place.

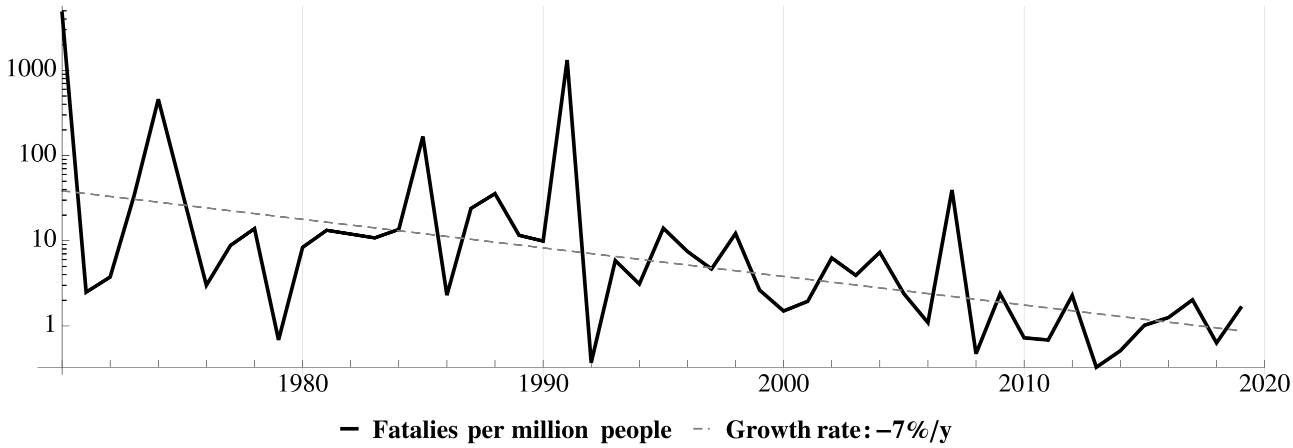

Figure 5: Natural Disaster Individual Risk in Bangladesh

A.3 United States

The US appears to be an oversampling outlier with respect to event frequency and financial risk. Indeed, the US landmass occupies 6% of the world emerged land so that the share of hazards

[23] Although Sidr was comparable in strength with Gorky, its landfall was also into a less inhabited area.

coefficient	estimate	st dev	t-Stat.	P-Value
α	131.0	27.09	4.836	0.00001
β	-0.065	0.014	-4.759	0.00001

Table 4: Econometric Trend estimation for Bangladesh

passing over the US should be a nearby figure. At the same time, the US makes up a quarter of the world GDP over recent decades; one would then expect its share of natural disaster losses to hover between 6% and 25%. Yet, the US occupies more one half of the entries in SwissRe's yearly list of 20 most costly insurance losses (over the decade 2008-2017). This excess, in all likelihood, is due to the greater penetration of insurance in the US. Looking further back in time, the share of US natural disasters in the EM-DAT database has been greater than its share of population or share of potential hazards. This oversampling may be due to history (disaster databases started in US universities from mostly local sources), a far reaching statistical apparatus and greater newspaper density for reporting. Researchers have thus been more efficient at identifying disasters in the US than elsewhere. This finding makes any database of world disasters unbalanced; at the same time, the higher quality of coverage in the US offers an opportunity to test for trends with a greater statistical confidence.

All our information is sourced from a variety of departments at NOAA. Flood casualties and losses are extracted from the Hydrologic Information Center. Losses being expressed in 2014$ using with the *Construction Cost Index* of consultancy business “Engineering News-Record“, we use this very index to reconstruct a nominal dollar losses series. Some likewise ancient information about lightning, tornadoes, tropical and winter storms is collected from NOAA (2019) and aggregated here as $disaster^*$. For tropical storms, we additionally borrow the list of losses (in nominal dollars) published by Pielke et al. (2008) and continued by Klotzbach et al. (2018). We also use the individual storm reports from NOAA (2018) for missing years and updates recently published.

As may be appreciated on Figure 6, the individual risk of dying in a flood has fallen even though some years featured dramatic events with a large number of casualties. The econometric analysis displayed in Table 5 is insensitive to the starting year, whether the low 1932 or the high 1934.[24] The total over all natural disasters (excluding heat and cold waves victims) reveals a similar picture of a statistically significant downward trend. The econometric test concludes to a downward trend for the risk of dying in a disaster of natural origin (virtually certain) and floods (very likely). As a matter of comparison, this risk currently stands below one casualty per million population whereas car accidents claim 110 times more lives and the (human induced) opioid overdose epidemic 220 times more fatalities (cf. CDC (2018)). These figures might help authorities establish priorities for

[24]The data goes back to 1903 but several years feature zero victims which is highly suspicious. We thus set the starting point to the 1930s when statistics start to display a greater regularity.

public safety actions.

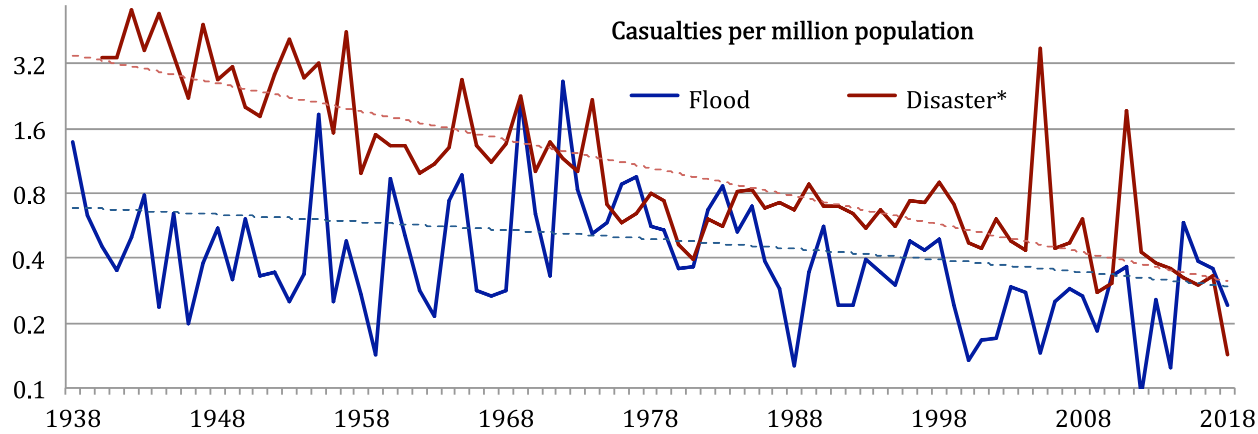

Figure 6: Natural Disaster Individual Risk in the USA

Individual Risk Trend	slope	st dev	t-Stat.	P-Value
Flood	-0.004	0.002	4.520	0.037
Disaster*	-0.041	0.005	84.03	0.000

Table 5: Econometric test for US Individual Risk over 1940-2018

Next, we consider the property risk relative to floods and storms (including hurricanes) using the US nominal GDP sourced at the Bureau of Economic Analysis. Figure 7 displays the 5-year moving average to smooth out the curve as many years feature near zero hurricane losses.

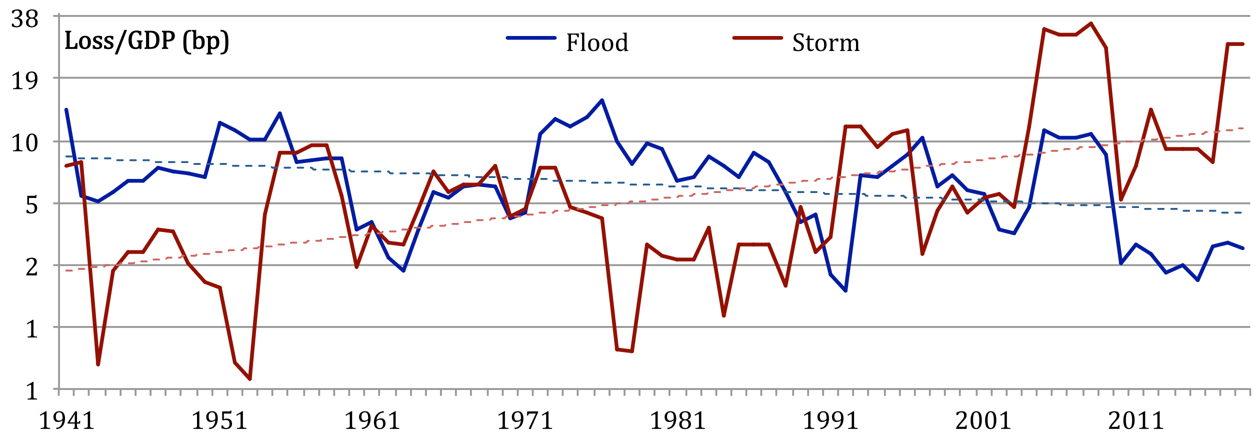

Figure 7: Natural Disaster Financial Risk in the US

Table 6 presents the results of the econometric test performed upon the original time series. Whereas the property risk from floods, a frequent occurrence, has been falling (very likely), that of storms, rare but devastating events, has gone up (very likely). Interestingly, the sum of those two risks which is probably close to the total for natural disasters in the US, is solely “likely” to be trending up. It is thus safe to conclude to an absence of statistically significative positive trend for property risk in the US (although there is a hint).

Property Risk Trend	slope	st dev	t-Stat.	P-Value
Flood	-0.008	0.004	4.739	0.032
Storm	0.022	0.008	7.112	0.009
Flood+Storm	0.014	0.010	2.167	0.145

Table 6: Econometric test for US Property Risk over 1932-2018

Interpreting the previous dual finding is challenging. On the one hand, US residents have left the inland areas bordering rivers in favor of the coast lines during the recent decades, thus moving their riches from flood prone areas to hurricane prone ones.[25] On the other hand, flooding impact, a very old menace, has probably been mitigated, like in most advanced countries, by prevention efforts such as restrictive zoning for new construction and defensive infrastructure building. It may also be the case, as the media reveal, that no such effort has ben seriously undertaken in coastal areas, thus precipitating the catastrophic effect of hurricanes. Disentangling these opposing causes require using local (county level) property information and geolocalized hazard data (cf. Dinan (2017)). At the outset, we may be observing a typical economic phenomenon whereby storms are indeed becoming costlier but, since "all thing else" are not equal, the overall share of American wealth destroyed every year by natural disasters may not yet be increasing.

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