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ON FLOOD RISK MANAGEMENT ACROSS SOCIO-ECONOMIC ENVIRONMENTS

GESTIÓN DEL RIESGO POR INUNDACIONES EN PAÍSES CON DISTINTAS CARACTERÍSTICAS SOCIOECONÓMICAS

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Abstract

In this paper, we discuss the insuring of flood losses across socio-economic environments, by pooling their risk exposures at continental and global levels. Grouping regions by their flood count over the last century, we cluster countries based on estimations of their value-at-risk, minimising the total value-at-risk from all clusters, as in Prettenthaler, Albrecher, Asadi, and Köberl (2017). Using heavy-tailed distributions to model the losses (presented as percentages of GDPs and adjusted to inflation), we seek an optimal risk pooling strategy across countries, irrespective of their socio-economic status. The financial benefits for such risk sharing, both at the continental and global levels, are quantified by the overall corresponding values-at-risk with or without pooling. We advocate this risk partner- ship across socio-economic environments, as a mechanism for reducing risk premiums and increasing efficiency in disaster response.

Keywords: flood risk, risk pooling, value-at-risk, heavy-tailed distributions.

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Resumen

En este artículo se analiza el seguro en caso de inundación en diferentes países con diferentes niveles socio-económicos combinando sus exposiciones al riesgo, en primer lugar, a nivel continental y luego a nivel global. Después de juntar las regiones según su número de inundaciones durante el último siglo, agrupamos los países en función de estimaciones de su valor en riesgo, minimizando el valor total en riesgo de todos los grupos, como en Prettenthaler, Albrecher, Asadi, and Köberl, (2017). Utilizando distribuciones de colas pesadas para modelar las pérdidas (presentadas como porcentajes del PIB y ajustadas a la inflación), buscamos una estrategia óptima de agrupación de riesgos entre países, independientemente de su situación socioeconómica. Los beneficios económicos de dicha distribución de riesgos, tanto a nivel continental como mundial, se cuantifican mediante los correspondientes valores en riesgo con o sin agrupación. Recomendamos esta agrupación de riesgo para todos los países, como un mecanismo para reducir las primas de riesgo y aumentar la eficiencia en la respuesta a desastres.

Palabras clave: riesgo de inundación, la agrupación de riesgos, valor en riesgo, distribuciones de cola pesada.

1. Introduction

Climate-related disasters made up 91% of all recorded disasters between 1998 and 2017, with floods accounting for 43% of climate events (Wallemacq & House, 2017). Affecting over 2 billion people globally with associated economic losses of 656 billion USD (Wallemacq & House, 2017), floods are the most frequently occurring disaster type with consequences for more individuals than any other. Addressing the significance of flood risk on the global scale is therefore crucial for sustaining economic development.

The International Disaster Database EM-DAT documents the occurrence and impacts of mass disasters throughout the world. Of all 5266 floods recorded in the database, spanning the years 1900 to 2020, 305 occurred in India and 304 in China. When restricted to include only those events with recorded total damages (of which there are 1770 floods), China places 51 times in the top 10% of floods associated with the highest damages, followed by the USA and India with 19 and 15 events, respectively. Although the highest totalling 10% of floods occurred between 1931 and 2020, 76 of the 177 events were experienced within the last

10 years. The flooding of the Yangtze river in 1998 is associated with the greatest flood damages in China, second only to the 2011 flooding of Thailand. Although absolute economic losses are often greatest in upper-middle and high income countries due to increased asset exposure, considering losses relative to GDP the significance of the loss shifts to countries of lower economic development (Wallemacq & House, 2017), with the impact of floods increasing with the vulnerability of the environment (Broberg & Hovani-Bue, 2019).

Wallemacq and House (2017) highlight the need to acknowledge the systematic under-reporting of flood data by low income countries. For flood events occurring between 1998 and 2017, low income countries reported just 13% of disasters, whilst the report rate in high income countries was 53%. Discussion of loss significance and future flood predictions in low income countries is therefore based on a small sample of the true disaster environment.

Defined as the product of hazard (the flood, its intensity and probability of occurrence), exposure (the population and assets at risk) and vulnerability (the ability of the exposed to deal with the hazard) (Kron, 2005), flood risk has increased rapidly over time. Changes in each of the three risk components have initiated variations in the frequency and extremity of flood events. Demographic characteristics, socio-economic status and health are found to be the three leading empirical indicators of social vulnerability to floods (Rufat, Tate, Burton & Maroof, 2015). Although climate change is widely accepted as a key element in the global increase in flood risk, the influence of socio-economic changes on the significance of the risk means the relationship between climate change and flood risk is not transparent. Population growth, wealth and urban development in risk- prone areas experiencing rapid economic growth have significantly raised the exposure and vulnerability of communities to extreme floods (Jongman, Ward & Aerts, (2012) with this exposure increasing at a faster rate than the potential for strengthening risk reduction measures (ISDR, 2009).

In line with the severity of the implications of increasing flood risk, significant literature exists on the study of the changing flood environment. Focusing on flood occurrence in Europe, Blöschl et al. (2020) report the current flood-rich period to be amongst the most significant of the last 500 years, with an increased flood phase temperature in contrast to historical periods. Douglas et al. (2008) present flood risk perceptions of particularly vulnerable populations through a vulnerability analysis of five flood-prone cities in Africa. The need for formal flood risk interventions in such countries is highlighted in this study, and heightened by the prevelance of informal settlements and high rates of population and urban growth in flood prone areas (Field, Barros, Stocker & Dahe, 2012). For a thorough review of literature on the human impact of floods based on events between 1980 and 2009, see Doocy, Daniels, Murray and Kirsch (2013).

Whilst attribution of trends in disaster losses to anthropogenic climate change is a debated topic (Bouwer, 2011; Visser, Petersen & Ligtvoet, 2014) the impact of climate change on flood risk hazard cannot be denied, with unparalleled increases in the frequency and severity of flood events expected in the coming years due to the intensification of the hydrological cycle (Field et al., 2012). The non-uniformity of the climate-risk relationship creates the need for region specific flood mitigation measures. Projected increases in flood risk in Southeast Asia are largely associated with estimated levels of socio-economic development, where exposure environment predictions place Asia as the most exposed region with respect to population (Hanson et al., 2011). Economic consequences of flood events in African countries on the other hand are expected to experience a climate driven rise (Winsemius et al., 2016).

1.1 Flood insurance

Flood insurance is essential to any flood risk management plan, providing a method for transferring risks associated with extreme flood events away from the exposed. Alongside improving financial preparedness, participation in risk transfer schemes has the capacity to influence behaviours and approaches to flood risk (Surminski, 2014). Adoption of risk reduction measures was not traditionally encouraged by insurers, however establishing guiding principles for the building of insurance programs, Kunreuther and Michel-Kerjan (2009) highlight the importance of encouraging such participant engagement in order to reduce vulnerability. The use of insurance as a risk management tool for lowering vulnerability is supported throughout the literature, see for Hudson, Botzen and Aerts, (2019), Surminski and Thieken (2017) and Surminski and Oramas-Dorta (2014). Behaviour change due to insurance participation may also move negatively as a result of moral hazard, where the insured behaves in a risky fashion, increasing the probability a loss is incurred (Prettenthaler et al., 2017). Moral hazard poses a potential risk for insurers even at the government level (Surminski, 2014).

In line with the varying socio-economic environment, risk transfer measures differ from country to country. Private schemes are common in the United Kingdom and Germany, whilst low-income countries generally rely on government and international aid to manage the consequences of extreme flood events (Michel-Kerjan & Kunreuther, 2011) (government relief is also the only source of financial support in the Netherlands despite a high level of flood risk

(Michel-Kerjan, 2010)). To reduce the reliance of flood victims on public assistance in the United States, the National Flood Insurance Program (NFIP) was introduced in 1968 following a series of severe floods. At the time, private insurers considered the offering of flood risk protection an unattractive form of coverage due to the dependent nature of claim occurrence and severity (Michel-Kerjan, 2010).

Whilst the importance of insurance in high income countries is widely acknowledged and well established, translating these principles to low and lower-middle income countries requires significant work. Implementation of innovative risk transfer mechanisms such as microinsurance and index-based insurance in low and middle income countries helps to improve the availability of insurance in such societies (Kron, 2009). Surminski and Oramas-Dorta (2011) present a detailed discussion of existing risk transfer schemes documented in the ClimateWise Compendium[b], a resource detailing natural hazard risk initiatives in low and middle income countries.

Income, product price and risk perception are three fundamental determinants of insurance demand (Browne & Hoyt, 2000). In relation to natural disasters, risk attitudes significantly influence the willingness of individuals to purchase insurance (Surminski, 2014). Probability of loss and disaster experience are positively correlated with insurance demand (Browne & Hoyt, 2000; Kunreuther, 1984), whilst certainty of governmental relief decreases the likelihood of purchase (Crichton, 2008; Paudel, 2012). Referred to as charity risk, the latter is of particular concern in relation to flood insurance (Raschky, Schwarze, Schwindt & Zahn, 2013). Ranger and Surminski (2013) discuss drivers of non-life insurance demand, with a focus on the impact of climate change. In relation to low income countries, non-performance risks, insurer trust, financial literacy and the use of informal risk-sharing mechanisms all contribute to the low uptake rate of insurance schemes (Eling, Pradhan & Schmit, 2014)

[b] "Compendium of disaster risk transfer initiatives in the developing world", 2020, https://www.cisl.cam.ac.uk/business-action/sustainable-finance/climatewise/pdfs/climatewise-compendium-of-disaster-risk-transfer.xlsm/view

Parallel to insurance demand, insurance penetration varies significantly by country (Outreville, 2013) and is positively correlated with income level (Ranger & Surminski, 2013). Of the ten most serious floods by economic loss between 2008 and 2017 [2], the percentage of insured losses ranges from 1.5% in China in 2010, to 36.4% in Australia in 2010/11. Addressing the impact of climate change on flood risk in Mumbai, Ranger et al. (2011) estimate a reduction of the indirect effects of a 1-in-100 year flood event by almost 50% through increase of insurance penetration to 100%. The study recognises the importance of risk mitigation measures, predicting a 70% reduction in flood losses through the upgrading of drainage systems. Improvements in penetration rates may also be observed through mandatory flood insurance schemes. Comparing the characteristics of catastrophe insurance systems in ten countries around the world, Paudel (2012) list mandatory insurance as one of their recommendations for policymakers, following analysis of insurance products with varying public-private balance. Government involvement and the mapping of risks are also included as key factors for the improvement of insurance mechanisms. “Option” and “bundle” insurance systems, favoured in countries including Belgium, Germany and Italy, and the UK, Japan, Portugal and Spain, respectively, are defined by Crichton (2008) as two insurance categories. Whilst the option system induces an environment for adverse selection and has low uptake rates, bundling enables alleviation of excessive rate increases through the diversification of risks over time, disaster type and region, and is associated with much higher penetration.

1.2 Risk pooling

Geographical location is a significant determinant of the nature and timing of the occurrence of a particular hazard. Catastrophe risks are therefore naturally diversifiable when considering a large geographical area. Exploitation of this principle in the form of insurance risk pooling facilitates the response of member countries to certain yet unpredictable risks through the group management of their risk via the pool. The risk pooling mechanism improves the predictability of funding flows and al- lows for the spread of disaster costs, eliminating any unpredicted budget reallocation need due the requirements of crisis response (Broberg & Hovani-Bue, 2019). Investigating hypothetical risk pooling schemes in low and middle income countries, The

[2] “A world at risk: closing the insurance gap”, 2018, https://www.lloyds.com/news-and-risk-insight/risk-reports/library/understanding-risk/a-world-at-risk

World Bank [3] reveal a reduction in the capital requirements of pooled risks versus non-pooled risks with a consequent reduction in risk premiums. Increased efficiency of disaster response through participation in risk pools greatly benefits ex- posed communities, with government aid in the traditional setting often deemed insufficient (Linnerooth-Bayer, Mechler & Pflug, 2005; Oxfam, 2005).

Regional risk pools were first established in 2007 with the Caribbean Catastrophe Risk Insurance Facility, a government risk-sharing platform and the first ever multi-country risk pool. Created in response to the devastation of Hurricane Ivan in 2004, the scheme allows member countries to move away from their reliance on post-disaster humanitarian assistance through affordable and effective management of their catastrophe risk exposure. Costs are reduced by at least half the expected cost of equivalent coverage purchased individually per country, from the global market (Mahul & Signer, 2014). Further expansion of the insurance risk pooling scheme market following the success of CCRIF include the Pacific Catastrophe Risk Insurance Pilot (PCRIP) (2013) and the African Risk Capacity (ARC) (2014). Parametric insurance policies form the basis of existing risk pooling schemes (Pillay, 2016), reducing moral hazard yet increasing basis risk, with the potential for some losses to fail to satisfy the payout criteria. Where the CCRIF and PCRIP aim to provide immediate financial support in the event of an unexpected disaster, the ARC focuses on the occurrence of droughts. The gradual nature of this hazard requires alternative approaches for risk mitigation. Following Hurricanes Irma and Maria in September 2017, CCRIF SPC (redefined after an expansion of coverage into Central America in 2014) provided payouts of 29.6 million USD to six Caribbean counties in less than 15 days. In 2015, Cyclone Pam caused damages equivalent to more than 60% of GDP in Vanuatu in the South Pacific. Enabled through the country's participation in the risk pooling scheme, 2 million USD (eight times the government's emergency provision) were received from PCRAFI seven days after the disaster [4].

In this study, we aim to analyse flood risk on a global scale. Using data from the Emergency Events Database (EM-DAT) and following a similar approach to Prettenthaler et al. (2017), we propose a risk pooling methodology

[3] "Sovereign Catastrophe Risk Pools: World Bank Technical Contribution to the G20" TheWorldBank,2017,https://openknowledge.worldbank.org/handle/10986/28311

[4] "What Makes Catastrophe Risk Pools Work: Lessons for Policymakers", The World Bank, 2017, https://www.worldbank.org/en/news/feature/2017/11/14/what-makes-catastrophe-risk-pools-work

at the worldwide and continental levels. Grouping regions by event frequency, we cluster countries based on estimations of their value-at-risk, minimising the total value-at-risk for each cluster. We first present the data set used in the analysis, the fitting of the heavy-tailed distributions to flood events and value-at-risk estimations for each country in Section 2. We will then describe the risk pooling and clustering methods in the global (Section 3) and continental (Section 4) cases, before concluding the paper in Section 5.

2. Data and risk analysis

2.1 Data analysis

Our analysis is conducted on flood records stored in the Emergency Events Database (EM-DAT), launched by the Centre for Research on the Epidemiology of Disasters (CRED) in 1988 [5]. This database has collected information on global catastrophic events since 1900. The data set is publicly available and well maintained, with frequent event updates. In this research, we focus on worldwide flood events dating back to as early as 1903, with the analysis carried out on data collected up to Aug 15, 2020. During the initial cleaning of the data, missing Consumer Price Indices (CPIs) were added to the data set using the Organization for Economic Cooperation and Development (OECD) Statistics CPIs Complete database[6] and the International Monetary Fund (IMF) Country Indexes and Weight database [7]. Once the complete set of CPIs were obtained, loss amounts adjusted for inflation were computed. All loss values used in the analysis are therefore adjusted for inflation and given in US dollars.

The flood data spans a period of over 100 years, countries have therefore experienced political changes and geographical renaming. For the purpose of this study, we identified event locations at a granular level, observing where the floods took place and combining losses within the same geographical areas. This allowed us to merge events which occurred in various locations corresponding to a single geographical area. For instance, floods in ‘Germany Federal Republic’ were combined with those in ‘Germany’. For floods in the ‘Soviet Union’, we looked further into event locations and found that flood

[5] https://www.emdat.be/
[6] https://stats.oecd.org/
[7] https://data.imf.org

occurred in what is now known as Georgia, whereas the rest occurred in the existing Russian territory. When preparing the dataset, we first filtered out countries with no more than 5 flood incidences recorded since 1903, leaving 70 countries for the analysis. We then aggregated the incurred losses per year for each country. Reserves are usually decided on a yearly basis at an aggregated level, we therefore fit the annual losses for each country and calculate their value-at-risk (VaR).

Heavy-tailed distributions are often used to model extreme or rare events, e.g. earthquakes, tsunamis, hurricanes and floods, amongst others. In this analysis, we normalise the global loss data for the 70 countries or territories by their overall gross domestic product (GDP), adjusting for inflation, and fit the normalised data to a number of heavy-tailed distributions (see Appendix). We adopt a similar method to that used in Prettenthaler et al. (2017) and divide the countries into two groups. Countries in the first group generally have more frequent floods and thus more observed data to carry out the fitting. Countries with no more than 10 floods over the past century are assigned to the second group. A detailed list of the countries in each group is presented in figure 1.

Group 1					
Algeria	Canada	Honduras	Malaysia	Romania	United Kingdom
Argentina	Chile	India	Mexico	Russia	United States
Australia	China	Indonesia	Nepal	South Africa	Viet Nam
Bangladesh	Colombia	Iran	New Zealand	Spain	
Bolivia	Ecuador	Italy	Nigeria	Sri Lanka	
Brazil	France	Japan	Pakistan	Tajikistan	
Cambodia	Germany	Korea	Philippines	Thailand	

Group 2				
Afghanistan	Fiji	Laos	Peru	Turkey
Austria	Georgia	Malawi	Poland	Ukraine
Bulgaria	Greece	Morocco	Portugal	Venezuela
Costa Rica	Hungary	Mozambique	Slovakia	Yemen
Czech Republic	Jamaica	Niger	Sudan	
Dominican Republic	Kazakhstan	Panama	Taiwan	
Ethiopia	Kenya	Paraguay	Tunisia	

Figure 1. Groups 1 & 2, Determined by the Number of Data Points per Country.

For countries in the first group, rather than applying maximum likelihood estimation (MLE), we adopt maximum goodness-of-fit estimation (MGE). MGE is also referred to as the minimum distance estimation method, as it seeks to minimise the discrepancy between the reference cumulative distribution function (CDF) F and the empirical distribution function (EDF) F_n (Luceño, 2006). An advantage of using this approach is that we have flexibility in choosing the appropriate distance metrics. The distance can be measured using statistics such as the Kolmogorov-Smirnov (KS) statistic

$$D_n = \sup_x |F_n(x) - F(x)|,$$

or statistics resulting from

$$W_n^2 = n \int_{-\infty}^{\infty} \psi(x) \left(F_n(x) - F(x)\right)^2 \mathrm{d}F(x)$$

for different weight functions $\psi(x)$. When $\psi(x) = 1$, the statistic W_n^2 is the Cramér-von Mises statistic $n\omega^2$. When $\psi(x) = 1/x(1 - x)$, the statistic W_n^2 is the Anderson-Darling statistic A_n^2, extensively studied by Anderson and Darling (1952), Anderson and Darling (1954). The statistic A_n^2 gives heavy weight to the tails and should be powerful against alternatives in which the true distribution and the reference distribution disagree near the tails of F.

2.2 *Risk analysis*

Value-at-risk (VaR) and expected shortfall (ES) are common risk measures. In this analysis, VaR is calculated after making the appropriate distribution choice for each country. The VaR at level β is defined as the solution to the following equation for x

$$\mathbb{P}(X < x) = \beta \quad \Rightarrow \quad \mathrm{VaR}_\beta(X) = x = F_X^{-1}(\beta).$$

Expected shortfall is the most prominent alternative to VaR, and is more sensitive to the shape of the tail of the loss distribution. It is defined as the following conditional expectation

$$\mathrm{ES}_\beta(X) = \mathrm{E}\left[X | X > \mathrm{VaR}_\beta(X)\right],$$

where β is the confidence level.

Since we will be working with VaR for measuring catastrophe risks, the right-tail goodness-of-fit plays a key role. As suggested in Chernobai, Rachev and Fabozzi (2005) we implement the MGE with a modification of the Anderson-Darling statistic proposed by Sinclair, Spurr and Ahmad (1990) which emphasizes the discrepancies between the empirical distribution F_n and F in the right tail. This modified statistic is also known as the 'right-tail Anderson-Darling 2nd order' statistic and is defined as

$$AU_n^2 = n \int_{-\infty}^{\infty} \frac{(F_n(x) - F(x))^2}{(1 - F(x))^2} \, \mathrm{d}F(x).$$

The 'best' choice of distribution is based on the results of the modified Anderson-Darling test statistics. The above quadratic version AU_n^2 adds more weight to the right tails while the left-tail fitting is unimportant in our context. This could possibly lead to an overestimation of risks based on historical observations, yet such extra caution might be necessary due to the recent acceleration in climate change, particularly for countries with more frequent floods. Recall that countries in the second group have few data points. Applying other fitting approaches leads to very large biases. We therefore employ quantile matching estimation (QME) on these data. This method matches the empirical and theoretical quantiles at pre-specified levels. For our purpose, the 80% and 99.5% quantiles are matched for 2-parameter distributions, whereas the median was also added for 3-parameter distributions.

Fittings were attempted on 5 candidate parametric distributions, the log-normal distribution, the Weibull distribution, the Burr distribution, the Pareto distribution and the truncated Pareto distribution. Note that the support of all these random variables is defined on the positive real line, which meets our needs of modelling incurred losses. The final distribution for a country was chosen based on the Anderson-Darling goodness-of-fit test statistic. We built upon the fitting tools from the R package *fitdistrplus* (Delignette-Muller et al., 2015) and *actuar* (Dutang et al., 2008) and automated the fitting and distribution selection process for all 70 countries. We arrange the countries by continent, Africa, the Americas, Asia, Europe and Oceania, and we specify which group each country belongs to depending on the number of data points, as in figure 1. Fitting results in Table 1 - Table 5 contain information on the chosen parametric distribution, the VaR and ES derived from the fitted distribution (in million US dollars), GDP in 2019 (in million US dollars), and VaR as a percentage of GDP for each country. Several fitting plots in log-log scale are also presented alongside the tables which exhibit clear fitted curves particularly in the right tails. Note that we include the 99.5% VaR and the 99% Expected Shortfall (ES) for each country's flood risk in Tables 1 - 5.

Table 1. *African Countries*

Country	Group	Dist	VaR (m$)	ES (m$)	GDP (m$)	% GDP
Algeria	1	W	2,430	2,764	170,000	0.014
Ethiopia	2	B	8	8	96,108	0.000
Kenya	2	TP	351	351	95,503	0.004
Malawi	2	B	409	475	7,667	0.053
Morocco	2	P	307	325	119,000	0.003
Mozambique	2	W	1,345	1,445	14,934	0.090
Niger	2	P	204	216	12,928	0.016
Nigeria	1	LN	4,915	8,426	448,000	0.011
South Africa	1	W	4,018	4,602	351,000	0.011
Sudan	2	TP	392	392	18,902	0.021
Tunisia	2	P	765	809	38,798	0.020
Sum			15,144	19,813		
Africa		Weibull	2,533	2,750	1,372,840	0.002

Table 2. *Asian Countries*

Country	Group	Dist	VaR (m$)	ES (m$)	GDP (m$)	% GDP
Afghanistan	2	P	563	596	19,101	0.029
Bangladesh	1	W	14,918	16,855	303,000	0.049
Cambodia	1	TP	1,566	1,570	27,089	0.058
China	1	B	65,868	72,660	14,300,000	0.005
Georgia	2	P	51	54	17,743	0.003
India	1	B	35,977	52,973	2,880,000	0.012
Indonesia	1	LN	12,325	19,991	1,120,000	0.011
Iran	1	LN	26,428	41,029	463,000	0.057
Japan	1	W	35,555	41,833	5,080,000	0.007
Kazakhstan	2	P	160	169	180,000	0.001
Korea	1	P	203,273	Inf	1,640,000	0.124
Laos	2	TP	142	142	18,174	0.008
Malaysia	1	B	4,514	6,008	365,000	0.012
Nepal	1	W	2,139	2,560	30,641	0.070
Pakistan	1	W	22,980	26,205	278,000	0.083
Philippines	1	LN	12,248	29,161	377,000	0.032
Sri Lanka	1	LN	11,273	24,869	84,009	0.134
Taiwan	2	B	149	153	586,104	0.000
Tajikistan	1	LN	4,451	7,489	8,117	0.548
Thailand	1	B	216,132	Inf	544,000	0.397
Turkey	2	B	1,538	1,630	754,000	0.002
Vietnam	1	B	1,564	1,721	262,000	0.006
Yemen	2	TP	2,763	2,764	27,591	0.100
Sum			695,093	Inf		
Asia		Weibull	86,816	93,170	29,364,570	0.003

Table 3. *American Countries*

Country	Group	Dist	VaR (m$)	ES (m$)	GDP (m$)	% GDP
Argentina	1	W	7,716	8,214	450,000	0.017
Bolivia	1	B	3,047	3,779	40,895	0.075
Brazil	1	W	6,662	7,546	1,840,000	0.004
Canada	1	B	26,098	274,654	1,740,000	0.015
Chile	1	B	10,679	85,551	282,000	0.038
Colombia	1	LN	142,555	685,086	324,000	0.440
Costa Rica	2	TP	401	401	61,774	0.006
Dominican Republic	2	TP	72	72	88,941	0.001
Ecuador	1	LN	23,951	57,215	107,000	0.224
Honduras	1	B	967	1,124	25,095	0.039
Jamaica	2	W	175	182	16,458	0.011
Mexico	1	B	16,072	33,203	1,260,000	0.013
Panama	2	P	95	123	66,801	0.001
Paraguay	2	P	204	367	38,145	0.005
Peru	2	LN	3,193	5,186	227,000	0.014
United States	1	W	37,163	40,846	21,400,000	0.002
Venezuela	2	P	4,710	13,735	70,140	0.067
Sum			283,760	1,217,284		
Americas		Weibull	30,665	33,124	28,038,250	0.001

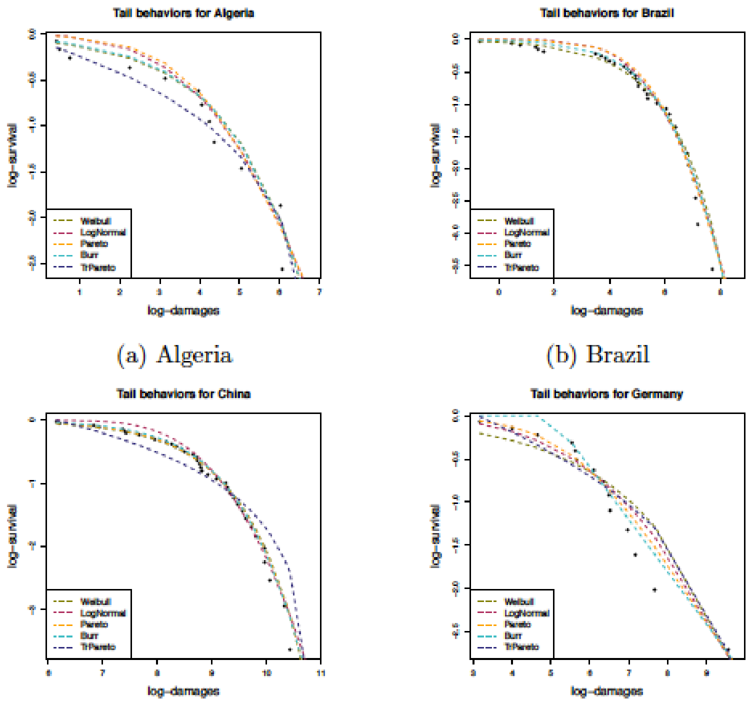
Table 4. *European Countries*

Country	Group	Dist	VaR (m$)	ES (m$)	GDP (m$)	% GDP
Austria	2	B	3,328	3,544	446,000	0.007
Bulgaria	2	TP	657	657	67,927	0.010
Czech Republic	2	P	3,701	3,915	246,000	0.015
France	1	P	5,617	5,964	2,720,000	0.002
Germany	1	P	548,917	Inf	3,850,000	0.143
Greece	2	P	972	1,028	210,000	0.005
Hungary	2	TP	634	634	161,000	0.004
Italy	1	B	425,771	Inf	2,000,000	0.213
Poland	2	P	6,063	6,414	592,000	0.010
Portugal	2	B	1,563	1,657	238,000	0.007
Romania	1	W	9,980	11,675	250,000	0.040
Russia	1	B	7,037	8,476	1,700,000	0.004
Slovakia	2	P	182	193	105,000	0.002
Spain	1	B	25,950	33,836	1,390,000	0.019
Ukraine	2	TP	1,161	1,161	154,000	0.008
United Kingdom	1	B	141,240	Inf	2,830,000	0.050
Sum			1,182,773	Inf		
Europe		Burr	56,978	69,076	16,959,927	0.003

Table 5. *Oceanian Countries*

Country	Group	Dist	VaR (m$)	ES (m$)	GDP (m$)	% GDP
Australia	1	LN	17,524	25,437	1,390,000	0.013
Fiji	2	W	98	101	5,536	0.018
New Zealand	1	W	894	982	207,000	0.004
Sum			18,516	26,520		
Oceania		Burr	20,742	66,323	1,602,536	0.013

In figure 1, we present the survival probabilities and flood losses in log-log scale for clearer visualization of the tail fittings. Due to the chosen distance metric, i.e., AD2R, the tail behaviours are carefully captured.



(a) Algeria (b) Brazil

(c) China (d) Germany

Figure 2: Log-log plots for fitting annual flood loss data by country. Black dots are observed values. Dashed curves are fitted parametric distributions.

3. Global risk pooling and clustering

Sums of the VaRs of individual countries in Table 1 - Table 5 represent the overall amount of capital that would be needed at the 99.5% safety level for each continent, in the case that each country deals with flood risks individually. Apart from Oceania, this amount is much larger than the VaR calculated on the basis of aggregated loss data for each continent, which incorporates the dependence structure between individual countries. Hence, there is a strong diversification potential for pooling flood risk across countries within each continent as well as cross- continent.

The main algorithm used to cluster the above 70 countries clusters according to flood risk in the form of annual aggregate losses. When a cluster is formed, we aggregate losses from all member states in this cluster by the same calendar year, as if we were treating the cluster as a 'country' with losses to be the sums of all its 'regions'. Our aim is to minimise the total VaR summed from all clusters. Let us represent the VaR for a number of clusters G as

$$\mathrm{VaR}_G = \min \sum_{k=1}^{G} \mathrm{VaR}\left(\sum_{i \in N_g} X_i\right),$$

where X_i denotes the annual aggregate flood loss for country i and N_g is the number of countries in a particular cluster g. Note that

$$\mathrm{VaR}(X_i + X_j) \neq \mathrm{VaR}(X_i) + \mathrm{VaR}(X_j), \quad \forall i,\, j \in N_g,$$

and in fact, since subadditivity does not always holds true for VaR, we cannot guarantee that the objective function always decreases by adding one country into the risk pool. ES is not chosen as the risk measure in this analysis since some ES values in Tables 1 - 5 are equal to infinity.

Unlike in Prettenthaler et al. (2017), our sample size of 70 is large. Investigating all possible clusters would be computationally infeasible. We therefore work with a heuristic algorithm to approach optimality. Borrowing the idea used in the hierarchical clustering algorithm, we propose our own algorithm with a number of modifications. The hierarchical clustering algorithm is described as follows. Its endpoint is a set of clusters, where all clusters are distinct from each other, and the objects within each cluster are broadly similar to one other. This algorithm is based on a certain measure of 'distance' between objects and in fact, our main adaptation lies in the distance metric. Under our setting, the measure of 'dissimilarities' between two countries/clusters will be the amount of reduction in risk (measured by 99.5% VaR) due to the clustering. We fuse countries with the largest reduction in VaR at each iteration.

From the global perspective, we will carry out the clustering separately for the two groups of countries mentioned earlier. Since different fitting approaches were applied to the two groups, we will also modify the clustering algorithms correspondingly. For clarity and ease of flow, we will use the following terminologies throughout the remainder of the paper.

Term	Meaning	Notation
Total VaR	Summation of VaRs from all current clusters	$\sum_{k=1}^{G} \mathrm{VaR}\left(\sum_{i\in N_g} X_i\right)$
Aggregate VaR	VaR of a specific cluster of countries whose flood risks have been aggregated	$\mathrm{VaR}\left(\sum_{i\in N_g} X_i\right)$
Sum VaR	Summation of VaRs from two clusters/singletons	$\mathrm{VaR}(X_i) + \mathrm{VaR}(X_j)$

3.1 Clustering algorithm

The algorithm for clustering Group 1 is presented in Algorithm 1.

Algorithm 1: Clustering Algorithm for Group 1

Result: Total VaR
Initialisation: Each country is a cluster on its own. Total VaR = Sum of individual VaRs for each country;
while max(*Sum VaR* − *Aggregate VaR*) > 0 *and current number of clusters* > *2)* **do**
- Identify each possible pairing of cluster/singleton;
- Calculate Sum VaR for each pair: $\mathrm{VaR}(X_i) + \mathrm{VaR}(X_j)$;
- Compute aggregate losses for each pair: $X_i + X_j$;
- Run the fitting procedures for Group 1 as described before on $X_i + X_j$ and calculate the Aggregate VaR for this pair: $\mathrm{VaR}(X_i + X_j)$;
- Fuse the singletons/clusters with the largest discrepancy between Sum VaR and Aggregate VaR; Update the clusters by treating the fused singletons/clusters as a new cluster.;

end

We adopt empirical VaRs instead of theoretical ones for Group 2 due to the unavailability of a sufficient number of historical data points. Consequently, we skip the whole fitting procedure, saving a significant amount of computing time. Note that the terminologies used in this algorithm are analogous to the ones displayed in the table shown earlier.

VaRs are simply replaced by empirical VaRs.

Algorithm 2: Clustering Algorithm for Group 2

Result: Total Empirical VaR

Initialisation: Each country is a cluster on its own. Total Empirical VaR = Sum of individual Empirical VaRs for each country;

while
max(*Sum Empirical VaR* − *Aggregate Empirical VaR*) > 0 *and current number of clusters* > *2)* **do**

- Identify each possible pairing of cluster/singleton;
- Calculate Sum Empirical VaR for each pair: $\hat{\text{VaR}}(X_i) + \hat{\text{VaR}}(X_j)$;
- Compute aggregate losses for each pair: $X_i + X_j$;
- Calculate the Aggregate Empirical VaR for this pair: $\hat{\text{VaR}}(X_i + X_j)$;
- Fuse the singletons/clusters with the largest discrepancy between Sum Empirical VaR and Aggregate Empirical VaR; Update the clusters by treating the fused singletons/clusters as a new cluster.;

end

The algorithm allows us to find ways of dramatically reducing Total VaRs at the beginning of the clustering, gradually reaching a point where the Total (Empirical) VaRs do not exhibit substantial reductions. This could be reflected in the dendrograms presented below (see Figure 3 and 4).

3.2 Clustering results and analysis

The dendrograms for both groups are displayed in Figures 3 and 4. A dendrogram provides a detailed summary of the clustering process. Since this is a hierarchical approach, we did not have to choose an optimal number of clusters throughout the algorithm. Instead, we could visualise the process, with the flexibility to determine the number of clusters from the dendrogram (see Figures 3 and 4). Note that normally in dendrograms, the vertical axis denotes the level of dissimilarity at which each cluster is formed. Under our setting, the amount of reduction in VaR after combining countries is analagous to dissimilarity. However, the larger the reduction, the lower the 'dissimilarity', and thus the earlier certain countries are fused. In this way, the dendrograms here intuitively present a hierarchical structure with countries fused at lower levels to be clustered first. The y-axis values, however, do not have as straightforward a meaning as the Euclidean distance in traditional dendrograms, yet they may still serve as a visual aid for the identification of clusters. The two groups clearly differ in the scale of their y-axes, in line with the reasoning behind their initial separation. Generally speaking, countries pooled together at the mini- mum fusing level are those with the greatest reduction from Sum VaR to Aggregate VaR. From a risk management perspective, this is when risk pooling is most effective. Pooling can be applied to earlier established clusters as well as singletons. We seek for paths of maximisation at each iteration, which could heuristically lead us to a global minimum while we iterate through the clustering process.

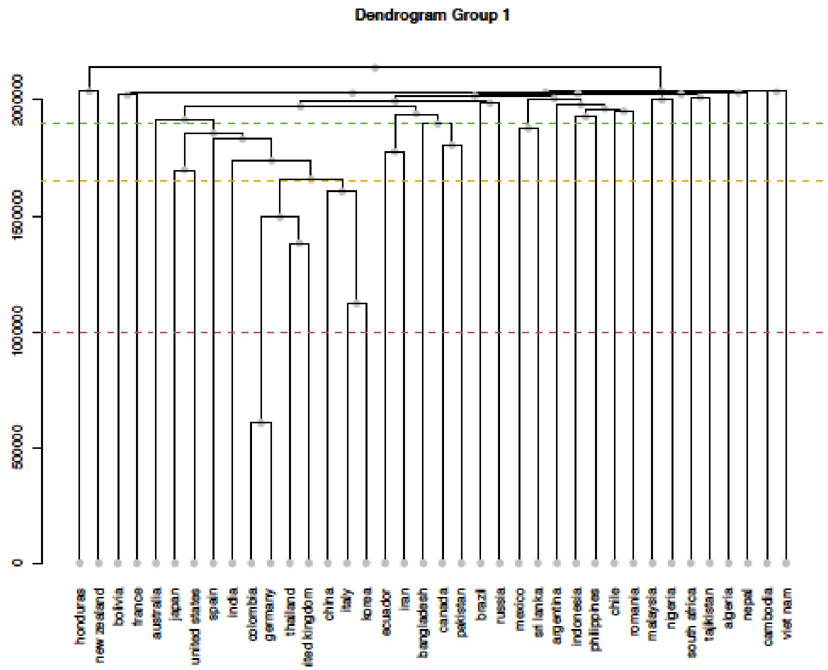


Figure 3: Clustering in Group 1.

Horizontal lines added to the dengrograms represent potential cuts at different fusing levels. Note that countries clustered earlier in the procedure are purposely placed at the centre of the graphs. For instance, for countries in Group 1, a cut at 1 million results in just one cluster consisting of Colombia and Germany. As we move along the y-axis, more clusters are formed. Line positions are arbitrarily set for the purpose of illustration. The benefit of this hierarchical clustering is that policymakers have the freedom to choose any fusing level at their own preference, with clusters formed accordingly. In practice, pooling together flood risk from different countries may not be as straightforward as simply combining their loss amounts. The process involves many administrative procedures and is dependent on the regulations and rules specified in each insurance policy. Our dendrograms offer such flexibility to the insurers.

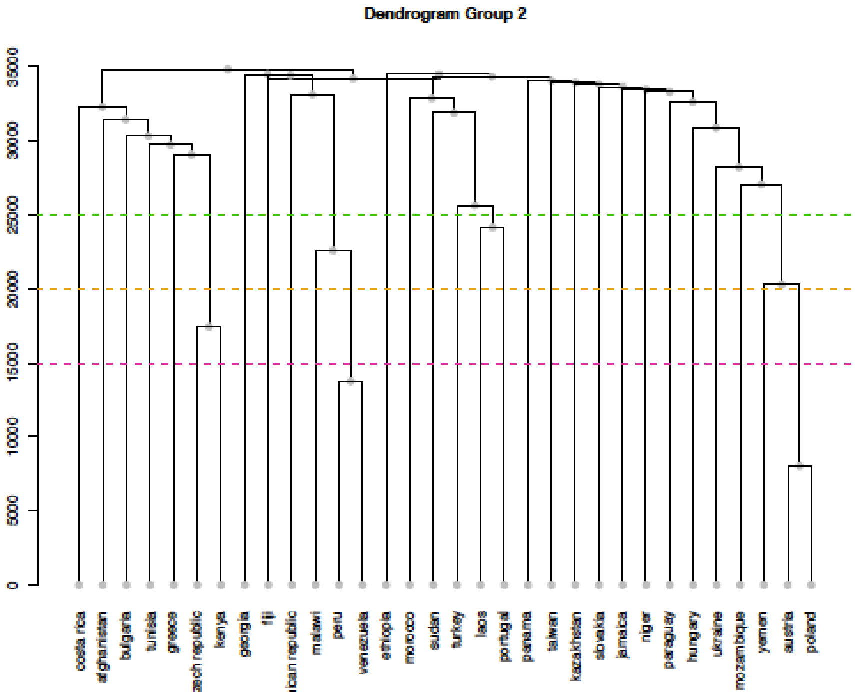


Figure 4: Clustering in Group 2.

Summarising our initial findings, we observe that the Total VaR global minimum could be achieved when almost all countries are pooled together, however its value does not reduce further after many iterations. This implies that a fewer number of countries could be pooled together in order to approach a value of Total VaR that is sufficiently close to its minimum. In regard to practical considerations, when the increase in other expenses overtakes the drop in VaR, it may no longer be worth pooling additional countries.

Nevertheless, our study facilitates the placing of the final cluster number decision into the hands of risk managers. Our clustering results demonstrated in the dengrograms could be used as an ordered reference list for pooling risks. For countries in Group 1, one might consider merging flood risks from Columbia, Germany, Thailand, the United Kingdom, China, Italy and South Korea, as they are clustered earlier in the process. We take these countries as an illustration. Suppose we choose a cut at around 1,650,000 m$. This cut leads to two clusters, presented in Table 6. In the table, one can also compare the Aggregate VaR to the Sum VaR for such cluster.

Table 6. *An Illustrative Example with a Cut of 1,650,000 m$.*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR
1	Columbia	142,555.3	1,048,844	70,976.31
	Germany	548,917.0		
	Thailand	216,131.9		
	United Kingdom	141,239.6		
2	Italy	425,771.40	694,912.4	67,778.34
	South Korea	203,273.14		
	China	65,867.89		

The clustering has indeed led to a significant reduction of risks. Recall that we used an estimation method which places extensive weight on the tails and could very likely lead to overestimation. This estimation was not only applied to individual losses, but also to the clustered data. The following table summarises the distributions chosen for individual countries and clusters, respectively.

Table 7. *An Illustrative Example Continued - Best fitted distributions*

Cluster	Countries	Individual Dist.	Aggregate Dist.
1	Columbia	Log-Normal	Weibull
	Germany	Pareto	
	Thailand	Burr	
	United Kingdom	Burr	
2	Italy	Burr	Weibull
	South Korea	Pareto	
	China	Burr	

Further clusters can be identified using the dendrograms in a similar way, including those in Group 2. For instance, a cut at level 15,000 m$ would result in two clusters: Peru pooled together with Venezuela, and Austria merged with Poland.

4. Risk pooling and clustering by continent

In this section, we use similar techniques to pool and cluster countries within each continent. Since there are only three countries considered in Oceania, we place all of them in one group for the following analysis. We divide Africa, the Americas and Europe into two groups, Group A and B, and Asia into three groups, Group A, B and C, depending on the number of data points. From the continental perspective, as in Prettenthaler et al. (2017) we are able to identify the clusters which give the smallest Total (Empirical) VaRs for each continent by investigating all combinations of clusters, since there are relatively fewer countries in each continent after grouping. Algorithms for clustering within the continent are the same as in Section 3.1.

Africa

For countries in Africa Group A, the results of the algorithm are presented in Table 8, proposing the creation of three clusters toreduce the flood loss risk.

Table 8. *Three clusters for Africa Group A*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Kenya	443.98	750.78	850.06	W
	Morocco	306.80			
2	Malawi	409.44	9,740.29	2,600.16	W
	Nigeria	4,914.92			
	South Africa	4,018.06			
	Sudan	397.87			
3	Algeria	2430.14	3,783.86	1,585.20	TP
	Ethiopia	8.28			
	Mozambique	1,345.44			
Total			14,274.93	5,035.42	

There are two countries in Africa Group B, Niger and Tunisia. The Sum Empirical VaR, 893.05 m$, is smaller than the Aggregate Empirical VaR, 2326.23$, suggesting no clustering should be used within this group.

Asia

Asia has the largest number of countries among all continents in this analysis and thus is divided into three groups. We consider three clusters for each Asian group (see Tables 9 to 11).

Table 9. *Three clusters for Asia Group A*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Philippines Vietnam	12,248.04 1,564.28	13,812.32	3,686.99	W
2	China India Korea Thailand	65,867.89 35,976.94 203,273.14 216,131.92	521,249.89	82,592.20	W
3	Indonesia Iran	12,325.32 26,428.30	38,753.62	14,522.82	B
Total			573,815.83	100,802.00	

Table 10. *Three clusters for Asia Group B*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Nepal Tajikistan	2,139.32 4,451.30	6,590.62	1,840.00	W
2	Bangladesh Japan Malaysia Pakistan	14,918.20 35,554.90 4,513.51 22,980.04	77,966.65	21,374.65	W
3	Cambodia Sri Lanka	1,566.18 11,272.97	12,839.15	1,590.92	TP
Total			97,396.42	24,805.57	

Table 11. Three clusters for Asia Group C

Cluster	Countries	Individual EmVaRs	Sum EmVaR	Aggregate EmVaR
1	Georgia	46.54	178.90	132.12
	Laos	132.36		
2	Kazakhstan	152.02	297.66	153.94
	Taiwan	145.64		
3	Afghanistan	553.13	4,649.72	2,525.04
	Turkey	1,531.85		
	Yemen	2,564.74		
Total			5,126.29	2,811.10

The Americas

We present only those results corresponding to the selection of three clusters in each group for the Americas. Tables 12 and 13 show that the Aggregate (Empirical) VaR reduces significantly after clustering.

Table 12. *Three clusters for the Americas Group A*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Chile	10,679.03	34,629.77	4,732.64	W
	Ecuador	23,950.74			
2	Argentina	7,716.31	93,711.00	31,775.93	W
	Brazil	6,661.87			
	Canada	26,098.03			
	Mexico	16,071.97			
	United States	37,162.82			
3	Bolivia	3,047.08	145,602.41	6,119.83	W
	Colombia	142,555.33			
Total			273,943.17	42,628.40	

Table 13. *Three clusters for the Americas Group B*

Cluster	Countries	Individual EmVaRs	Sum EmVaR	Aggregate EmVaR
1	Jamaica	174.58	378.26	208.32
	Paraguay	203.68		
2	Costa Rica	399.09	8,504.00	4,649.08
	Honduras	201.95		
	Peru	3,192.55		
	Venezuela	4,710.41		
3	Dominican Republic	62.44	157.30	96.59
	Panama	94.86		
Total			9,039.58	4,954.00

Europe

We present the results for two and three clusters for Europe Group A.

Table 14. *Two clusters for Europe Group A*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Austria	3,327.96	462,086.67	32,810.65	W
	Italy	425,771.40			
	Russia	7,037.48			
	Spain	25,949.83			
2	France	5,616.55	705,753.53	34,604.93	W
	Germany	548,916.96			
	Romania	9,980.41			
	United Kingdom	141,239.61			
Total			1,167,840.20	67,415.59	

Table 15. *Three clusters for Europe Group A*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR	Aggregate Dist.
1	Austria	3,327.96	13,308.37	11,994.26	W
	Romania	9,980.41			
2	France	5,616.55	695,773.12	38,468.72	W
	Germany	548,916.96			
	United Kingdom	141,239.61			
3	Italy	425,771.40	458,758.71	51,191.62	B
	Russia	7,037.48			
	Spain	25,949.83			
Total			1,167,840.20	101,654.60	

Three clusters are chosen for Europe Group B and the results are given in table 16.

Table 16. *Three clusters for Europe Group B*

Cluster	Countries	Individual EmVaRs	Sum EmVaR	Aggregate EmVaR
1	Hungary	558.18	729.72	621.30
	Slovakia	171.54		
2	Bulgaria	594.65	7,280.75	5,452.46
	Poland	5,525.42		
	Ukraine	1,160.68		
3	Czech Republic	3,394.87	5,782.77	3,395.40
	Greece	831.88		
	Portugal	1,556.02		
Total			13,793.25	9,469.16

Oceania

When considering Oceania, we place Fiji and New Zealand in one cluster and Australia in another, thus, Total VaR for the whole continent is 18,216.52 m$, slightly smaller than the Sum VaR in Table 5. Total VaR for the whole of Oceania is however 20,742 m$ (see Table 5) if all three countries are in the same cluster.

Table 17. *Two Clusters for Oceania*

Cluster	Countries	Individual VaRs	Sum VaR	Aggregate VaR
1	Fiji	97.91	992.30	692.98
	New Zealand	894.39		
2	Australia	17,523.54	17,523.54	17,523.54

5. Conclusion

As in Prettenthaler et al. (2017), we advocate the pooling of risks via joint insurance products across countries or regions, sharing the risk of floods in a reciprocal manner. We have exemplified the financial benefits for such risk sharing, both per continent and at the global level, by calculating the overall values-at-risk with or without pooling. Where our analysis uses a readily available data set, spanning flood records from all over the world from 1903 to 2020, and Prettenthaler et al. (2017) use European flood data from 1980 to 2014 for a European risk pooling analysis, the message is the same. We simply want to champion this cooperative risk management solution, which, alongside parametric insurance and microinsurance, can help everyone, but especially less developed socio-economic environments to be (more) shielded financially from the aftermath of natural disasters.

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7. References

Anderson, T. W., and Darling, D. A. (1952). Asymptotic Theory of Certain “Goodness of Fit” Criteria Based on Stochastic Processes. *The Annals of Mathematical Statistics*, 23(2),193–212.

Anderson, T. W., and Darling, D. A. (1954). A test of Goodness of Fit. *Journal of the American Statistical Association*, 49(268),765–769.

Beirlant, J., Alves, I. F., and Gomes, I. (2016). Tail fitting for truncated and non-truncated paretotype distributions. *Extremes*, 19(3),429–462.

Blöschl, G., Kiss, A., Viglione, A., Barriendos, M., Böhm, O., Brázdil, R., Coeur, D., Demarée, G., Llasat, M. C., Macdonald, N., et al. (2020). Current European flood-rich period exceptional compared with past 500 years. *Nature*, 583(7817):560–566.

Bouwer, L. M. (2011). Have disaster losses increased due to anthropogenic climate change? *Bulletin of the American Meteorological Society*, 92(1),39–46.

Broberg, M., and Hovani-Bue, E. (2019). Disaster risk reduction through risk pooling: the case of hazard risk pooling schemes. *The Cambridge Handbook of Disaster Risk Reduction and International Law*, 257–274.

Browne, M. J., and Hoyt, R. E. (2000). The demand for flood insurance: empirical evidence. *Journal of Risk and Uncertainty*, 20(3),291–306.

Chernobai, A., Rachev, S., and Fabozzi, F. (2005). Composite goodness-of-fit tests for left-truncated loss samples. *Handbook of Financial Econometrics and Statistics*, 575–596.

Crichton, D. (2008). Role of insurance in reducing flood risk. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 33(1),117–132.

Delignette-Muller, M. L., Dutang, C., et al. (2015). fitdistrplus: An r package for fitting distributions. *Journal of Statistical Software*, 64(4),1–34.

Doocy, S., Daniels, A., Murray, S., and Kirsch, T. D. (2013). The human impact of floods: a historical review of events 1980-2009 and systematic literature review. *Public Library of Science Currents Disasters*, 5.

Douglas, I., Alam, K., Maghenda, M., Mcdonnell, Y., McLean, L., and Campbell, J. (2008). Unjust waters: climate change, flooding and the urban poor in Africa. *Environment and Urbanization*, 20(1),187–205.

Dutang, C., Goulet, V., Pigeon, M., et al. (2008). actuar: An r package for actuarial science. *Journal of Statisticalsoftware*, 25(7),1–37.

Eling, M., Pradhan, S., and Schmit, J. T. (2014). The determinants of microinsurance demand. *The Geneva Papers on Risk and Insurance-Issues and Practice*, 39(2),224–263.

Field, C. B., Barros, V., Stocker, T. F., and Dahe, Q. (2012). *Man- aging the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change*. Cambridge University Press.

Hanson, S., Nicholls, R., Ranger, N., Hallegatte, S., Corfee-Morlot, J., Herweijer, C., and Chateau, J. (2011). A Global Ranking of Port Cities With High Exposure to Climate Extremes. *Climatic Change*, 104(1),89–111.

Hudson, P., Botzen, W. W., and Aerts, J. C. (2019). Flood insur- ance arrangements in the European Union for future flood risk un- der climate and socioeconomic change. *Global environmental change*, 58:101966.

ISDR (2009). Risk and poverty in a changing climate: invest today for a safer tomorrow. *United Nations International Strategy for Natural Disaster Reduction Global Assessment Report on Disaster Riskreduction*.

Jongman, B., Ward, P. J., and Aerts, J. C. (2012). Global exposure to river and coastal flooding: long term trends and changes. *Global Environmental Change*, 22(4), 823–835.

Kron, W. (2005). Flood risk = hazard · values · vulnerability. *Water International*, 30(1), 58–68.

Kron, W. (2009). Flood insurance: from clients to global financial markets. *Journal of Flood Risk Management*, 2(1), 68–75.

Kunreuther, H. (1984). Causes of underinsurance against natural disasters. *GenevaPapersonRiskandInsurance*, 9(31), 206–220.

Kunreuther, H., and Michel-Kerjan, E. O. (2009). *Managing catas- trophes through insurance: challenges and opportunities for reducing future risks*. Risk Management and Decision Processes Center, The Wharton School of the University ofPennsylvania.

Linnerooth-Bayer, J., Mechler, R., and Pflug, G. (2005). Refocusing disaster aid. *Science*, 309(5737), 1044–1046.

Luceño, A. (2006). Fitting the generalized pareto distribution to data using maximum goodness-of-fit estimators. *Computational Statistics & Data Analysis*, 51(2), 904–917.

Mahul, O. and Signer, B. (2014). Financial protection against natural disasters: from products to comprehensive strategies. *The World Bank - The Global Facility for Disaster Reduction and Recovery*.

Michel-Kerjan, E., and Kunreuther, H. (2011). Redesigning flood insurance. *Science*, 333(6041), 408–409.

Michel-Kerjan, E. O. (2010). Catastrophe economics: the national flood insurance program. *Journal of Economic Perspectives*, 24(4), 165–86.

Outreville, J. F. (2013). The relationship between insurance and economic development: 85 empirical papers for a review of the literature. *Risk Management and Insurance Review*, 16(1), 71–122.

Oxfam, G. (2005). 2005: A year of disasters. *Oxfam Policy and Practice: Agriculture, Food and Land*, 5(3), 1–7.

Paudel, Y. (2012). A comparative study of public-private catastrophe insurance systems: lessons from current practices. *The Geneva Papers on Risk and Insurance - Issues and Practice*, 37(2), 257–285.

Pillay, K. (2016). *Climate risk management: opportunities and challenges for risk pooling*, volume 2 of *Small States Digest*. Commonwealth Secretariat London.

Prettenthaler, F., Albrecher, H., Asadi, P., and Köberl, J. (2017). On flood risk pooling in Europe. *Naturalhazards*, 88(1), 1–20.

Ranger, N., Hallegatte, S., Bhattacharya, S., Bachu, M., Priya, S., Dhore, K., Rafique, F., Mathur, P., Naville, N., Henriet, F., et al.

(2011). An assessment of the potential impact of climate change on flood risk in Mumbai. *Climatic Change*, 104(1), 139–167.

Ranger, N. and Surminski, S. (2013). A preliminary assessment of the impact of climate change on non-life insurance demand in the BRICS economies. *International Journal of Disaster Risk Reduction*, 3, 14–30.

Raschky, P. A., Schwarze, R., Schwindt, M., and Zahn, F. (2013). Uncertainty of governmental relief and the crowding out of flood insurance. *Environmental and Resource Economics*, 54(2), 179–200.

Rufat, S., Tate, E., Burton, C. G., and Maroof, A. S. (2015). Social vulnerability to floods: review of case studies and implications for measurement. *International Journal of Disaster Risk Reduction*, 14, 470– 486.

Sinclair, C., Spurr, B., and Ahmad, M. (1990). Modified Anderson-Darling test. *Communications in Statistics - Theory and Methods*, 19(10), 3677–3686.

Surminski, S. (2014). The role of insurance in reducing direct risk: the case of flood insurance. *International Review of Environmental and Resource Economics*, 7(3-4), 241–278.

Surminski, S., and Oramas-Dorta, D. (2011). Building effective and sustainable risk transfer initiatives in low-and middle-income economies: what can we learn from existing insurance schemes?

Surminski, S., and Oramas-Dorta, D. (2014). Flood insurance schemes and climate adaptation in developing countries. *International Journal of Disaster Risk Reduction*, 7, 154–164.

Surminski, S., and Thieken, A. H. (2017). Promoting flood risk reduction: the role of insurance in Germany and England. *Earth's Future*, 5(10), 979–1001.

Visser, H., Petersen, A. C., and Ligtvoet, W. (2014). On the relation between weather-related disaster impacts, vulnerability and climate change. *Climatic Change*, 125(3-4), 461–477.

Wallemacq, P. and House, R. (2017). *Economic losses, poverty & disasters* 1998-2017. Centre for Research on the Epidemiology of

Disasters and United Nations Office for Disaster Risk Reduction.

Winsemius, H. C., Aerts, J. C., Van Beek, L. P., Bierkens, M. F., Bouwman, A., Jongman, B., Kwadijk, J. C., Ligtvoet, W., Lucas, P. L., Van Vuuren, D. P., et al. (2016). Global drivers of Future River Flood risk. *Nature Climate Change*, 6(4), 381–385.

8. Appendix

Heavy-tailed distributions used in this analysis:

1. The log-normal distribution has cumulative distribution function (cdf)
$$F_X(x;\mu,\sigma) = \Phi\left(\frac{\log x - \mu}{\sigma}\right), \quad x > 0,$$
where Φ is the cdf of a standard normal distribution.

2. The Weibull distribution has cdf
$$F_X(x;\tau,\alpha) = 1 - \exp\left((-x/\tau)^{\alpha}\right), \quad x > 0,$$
with parameters τ , $\alpha >$ 0.

3. The Burr distribution has cdf
$$F_X(x;c,k) = ck\frac{x^{c-1}}{(1+x^c)^{k+1}}, \quad x > 0,$$
with parameters c, $k > 0$.

4. The Pareto distribution has cdf
$$F_X(x;\alpha,\theta) = 1 - (\theta/x)^{\alpha}, \quad x \geq \theta,$$
with two parameters α, $\theta > 0$.

5. The truncated Pareto distribution (Beirlant, Alves, and Gomes, 2016). has cdf
$$F_X(x;\alpha,\theta,T) = \frac{1-(\theta/x)^{\alpha}}{1-(\theta/T)^{\alpha}}, \quad \theta \leq x \leq T,$$
where the upper bound T can be estimated from the data.