On Flood Risk Pooling in Europe*

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Abstract

In this paper we review and discuss some challenges in insuring flood risk in Europe on the national level, including high correlation of damages. Making use of recent advances in extreme value theory, we furthermore model flood risk with heavy-tailed distributions and their truncated counterparts, and apply the discussed techniques to an inflation- and building-value-adjusted annual data set of flood losses in Europe. The analysis leads to Value-at-Risk estimates for individual countries and for Europe as a whole, allowing to quantify the diversification potential for flood risk in Europe. Finally we identify optimal risk pooling possibilities in case a joint insurance strategy on the European level cannot be realized and quantify the resulting inefficiency in terms of additional necessary solvency capital. Thus the results also contribute to the ongoing discussion on how public risk transfer mechanisms can supplement missing private insurance coverage.

1 Introduction

Floods rank amongst the most wide-reaching and commonly occurring natural hazards in Europe. In the International Disaster Database EM-DAT (Guha-Sapir et al. [9]), flood events account for 36% of the damages recorded from natural disasters in Europe, followed by storm events (27%) and earthquakes (21%). The analysis in this paper is based on data obtained from Munich Re, NatCatSERVICE, 2014 though, which we would like to gratefully acknowledge here. Losses from floods show an increasing trend, which is mostly attributable to socio-economic factors, including population growth, economic development and construction activities in vulnerable areas. However, also climate change is expected to intensify the impacts of flooding (IPCC 2014 [8]). Hence, while representing a major issue already today, managing the risk of flooding is expected to become an even more important topic in the future.

Efficient flood risk management requires a combination of risk reduction, risk retention and risk transfer. The latter is defined as shifting the burden of disaster loss to another party (for instance by means of insurance). It represents an important instrument for

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managing the risk resulting from natural perils such as floods and can help mitigating or minimizing disaster losses. A well implemented plan how to spread economic risks from extreme events within society and/or transfer them from the victims to the financial markets is a fundamental adaptation measure that crucially decides on how impacts from climate change will finally disturb a society. Adequately designed, risk transfer mechanisms even have the potential to generate incentives for individuals as well as the collective to actively engage in risk reduction.

With respect to flood events (and natural catastrophes in general) a broad range of national risk transfer systems can be found in EU member states (see e.g. CEA [5], IBC [11], Jongman et al. [13], Keskitalo et al. [15], Maccaferri et al. ([20], Seifert et al. [32], Schwarze and Wagner [31] and Psenner et al. [28]). These vary considerably regarding their organizational structure and design elements. However, what most of these systems have in common is some kind of state intervention. The focus of the present paper is twofold: On the one hand it tackles the question what the role of the state (or a supranational body such as the EU) can be in the transfer of risk from floods, given that in many member states, there is not sufficient private insurance coverage for flood events. On the other hand, the paper tries to contribute to the flood risk modelling literature. Why are we combining these two quite separate issues? Firstly, the chosen risk modelling technique directly raises the question at what level a public intervention, such as acting as insurer of last resort, would make economic sense. Secondly, we try to argue, that if there is a role for public authorities to intervene in the risk transfer process due to market failure, then the topic of better availability of damage data supporting better risk modelling, that takes place in the public domain, becomes a crucial issue as well. There are several proprietary risk modelling packages around, the validity of which cannot be publicly debated since the model assumptions are not open to the scientific community. This might be considered a problem, if public funds are supposed to play a role in risk transfer mechanisms.

The remainder of this paper is structured as follows: Section 2 describes the key challenges of flood insurance and current approaches of dealing with them. Correlated risks of flooding are one such troublemaker, often leading to a breakdown of national insurance supply. However, correlation patterns also can be a positive contribution to handle risks, if we move to international cooperation in risk transfer. It is only in section 4, where we elaborate this thought in more detail as we need to have a concrete look into European flood risk on the national level first. This is carried out in section 3, where we use empirical flood loss data across Europe to calibrate a model and then determine loss quantiles as required for flood risk management. After a short overview of other modelling approaches and describing EVT techniques in the context of flood risk modelling we apply them to a suitably normalized data set of European flood loss data. A quantitative assessment of diversification potential for flood risk across European countries is given. As mentioned, Section 4 then discusses possibilities for the formation of sub-European pooling initiatives, in case a general collaboration on the European level is not feasible. Note that the quantitative model used in this paper does not take into account possibly changing flood risk due to climate change. However, the suggested changes in the flood risk transfer mechanism, that are substantiated by the quantitative modelling approach followed in this paper, can be seen as a possible major climate adaptation measure to increase the risk resilience of Europe, irrespective of whether the risk per se increases or not. Section 5 discusses the results and concludes.

2 Key challenges in flood insurance and strategies to handle them

From a supply-side point of view, particular conditions need to be fulfilled in order to be capable of maintaining the provision of a working insurance system, that is able to transfer, share and reduce risks (see e.g. Kunreuther and Freeman [18]; Kunreuther [17]; Prettenthaler and Albrecher [26]). Preconditions for the insurability of an event usually include the existence of a huge number of similar insurance entities, the determinability, measurability and randomness of the resulting damages – including that the occurrence and severity of the damage is beyond the control of the insured – as well as the calculability of the damage probability. Moreover, damages experienced by the insured entities should occur independently from one another, i.e. they should not hold any catastrophic damage potential. Lastly, premiums are to remain affordable.
Floods – like most other types of natural perils – however show various characteristics that make the sustainable provision of a working insurance system at affordable price challenging.

Small risk collective and adverse selection

One challenge relates to the creation of a risk collective of sufficient size (see e.g. Prettenthaler and Albrecher [26]). Floods tend to occur at the same place over and over again. If insuring against floods is voluntary, coverage tends to be demanded mainly in those areas that show an excessive damage probability. The overrepresentation of 'bad risks', i.e. with high loss probability, in the collective that demands insurance especially becomes a problem, if insurance companies have difficulties in screening clients (i.e. in case of information asymmetries e.g. due to lacking hazard maps) and/or are not able or allowed to charge risk-based premiums. This situation, where an individual's demand for insurance is positively correlated with its risk of loss and the insurer is unable to account for this additional risk in the price of insurance (also known as *adverse selection problem*) causes a vicious circle of increasing premiums and decreasing insurance demand of less endangered potential policyholders. Hence, adverse selection leads to a small risk collective and can threaten the economic viability of an insurance system. Common strategies to counteract the problems of too small risk collectives and adverse selection include the bundling of flood insurance with other kinds of (preferably) uncorrelated perils (e.g. fire or earthquakes) and risk-based premiums (see e.g. Prettenthaler and Albrecher [26]; Botzen [3]). The latter also ranks among the measures against moral hazard, a problem described below. However, it may result in unaffordable premiums in high risk zones.

Moral hazard

Besides adverse selection, there is a second consequence that may arise from information asymmetries between insurance companies and policyholders and reduce insurance demand: the problem of *moral hazard* (see e.g. Prettenthaler and Albrecher

[26]; Surminski [33]). It may occur after taking out an insurance policy and refers to a change in the insured's behaviour that causes the probability of loss to be higher than considered when setting up the contract. Examples for changes in the behaviour of the policyholder include reduced efforts of avoiding damages or of keeping them at a minimum. The problem of moral hazard – which is not exclusively related to flood risk but rather represents a key challenge for any insurance product – leads to a costly cycle of losses and hence makes it difficult to maintain the provision of insurance. Strategies in place to reduce the problem of moral hazard include the – however somewhat costly – monitoring of insured (see e.g. Botzen [3]) and the introduction of deductibles, co-insurance or upper limits on coverage. The effectiveness of the latter tools however remains unclear (Surminski [33]).

Charity hazard

The demand for insurance coverage may also be negatively affected by a lack of risk awareness (if e.g. information on the exposure is not sufficiently available) or by the so called *charity hazard*. The latter refers to the tendency of an individual to forego purchasing insurance or taking other precautions provided that ex post governmental assistance or aid from other sources can be anticipated in the event of a disaster (see e.g. Lewis and Nickerson [19]; Browne and Hoyt [4]; Prettenthaler and Albrecher [26]).

Correlated risks

Besides difficulties in creating a sufficiently large risk collective, there are further factors making the provision of flood insurance at an affordable price challenging: It is, for example, difficult to estimate uncertain low-frequency high-impact risks and, hence, the respective insurance premiums (see e.g. Paudel [24]). Surminski [33, p.260] mentions in this context that "flood is often regarded as the most technically challenging type of insurance due to a lack of accurate assessment of exposure, difficulty in estimating the probability of occurrence of an event and potential losses faced". Another challenge regarding the coverage of flood risk results from the possibility of a catastrophic damage. As natural hazards typically affect large connected areas, the resulting damages are correlated. Hence, large amounts of capital have to be available all at once in order to prevent insolvency on the one hand and to be able to guarantee coverage of the insured damages even in case of damage peaks on the other hand.Precautions such as the introduction of various limits, the development of insurance pools, reinsurance or the involvement of the international capital markets aim at limiting the damage burden for the single insurance company and at ensuring the required capacities (see e.g. Prettenthaler and Albrecher [26]). In the sections that follow, we will show how international cooperation in risk transfer may also help to reduce the capital needed to prevent insolvency.

State intervention

Despite the described possibilities of coping with the mentioned challenges, it might be difficult or even impossible for the private insurance sector to efficiently provide comprehensive insurance coverage for the whole population on its own. Small risk collectives, a lack of risk awareness among the population, adverse selection and moral hazard as well as the risk of loss accumulation contribute to the facts, (i) that insurance penetration related to flood risk is often very low, (ii) that coverage is strongly limited in many cases or only available at high costs and (iii) that only a small part of the losses resulting from a catastrophic event is covered by insurance. Due to these difficulties, different kinds and extents of state intervention have developed (see e.g. Paudel [24]), which include amongst others:

- Providing the necessary framework for private insurance companies to cover flood risk (e.g. through the provision of nation-wide hazard maps, risk-minimizing spatial planning and building regulations, legal framework for obligatory coverage extension or compulsory insurance, etc.)
- Subsidizing insurance premiums
- Acting as (re)insurer of last resort
- Providing ex-post ad-hoc aid (which, however, may lead to negative incentives such as charity hazard)
- Managing the insurance scheme
- Acting as monopolistic insurance provider

The adequate role of the state in a nation's risk transfer system is frequently discussed (see e.g. Paudel [24]) and a variety of systems has evolved in the past, ranging from a rather passive role of the state via the establishment of an adequate framework for the insurance industry through to an active role in compensating private damages (for comprehensive overviews see e.g. CEA [5], IBC [11], Jongman et al. [13], Keskitalo et al. [15], Maccaferri et al. ([20], Seifert et al. [32], Schwarze and Wagner [31] and Psenner et al. [28]). When taking an active role in compensating private damages, acting for instance as an insurer of last resort is seen as principally preferable to governmental ex-post ad-hoc aid (e.g. through compensation funds), since the latter is related to negative incentive effects. The (hypothetic) Solvency II compliant capital requirement for the state as an insurer of last resort is not necessarily much smaller than the Solvency II compliant capital requirement for a primary insurance pool, though: Prettenthaler and Albrecher [26] e.g. calculated both numbers for a Public-Private Partnership (PPP) suggested for Austria, where a national pool was supposed to cover damages up to 3 bn € whilst the government was responsible to cover the damage beyond that threshold, and the capital requirement proved to be about the same for both.

Thus, the state, even though it is the biggest possible risk collective, still may be overcharged. This does not come as a surprise, since the high (spatial) correlation of flood risk leads to high aggregate risk for any fund whose portfolio is not spatially diversified. But whilst the typical European nation states are composed of only a few river basins (if they belong to more than one at all), the European Union is composed of a big enough number of river basins, rainfall patterns and climatic zones. It only was logic thus, that the big flood events of 2002 led to the establishment of the European Union Solidarity Fund (EUSF). "*The EUSF supplements countries' own public expenditure to finance essential emergency operations. These include: restoring essential infrastructure e.g. energy, water, health and education; temporary accommodation and costs of emergency services to meet immediate needs; securing of prevention infrastructures, such as dams; measures to protect cultural heritage; clean-up operations.*

Damage to private property or income loss, considered insurable, is not covered" (EC Regulation No 2012/2002 and EU Regulation No 661/2014). In that way, the EU has also somehow become an insurer of last resort for the national public expenditures associated to floods. Clearly this engagement does not include the expenditures the member states incur in their own role as insurers of damage to private property. But at least there is a justification for extending the discussion on the role of the state from the level of individual member states to that of the EU as a supranational organization that especially can make use of the diversity of its member states in the sense of risk diversification, if any role is adopted. To make it clear: Since the state has to intervene anyhow, providing primary insurance or reinsurance on its own is not a completely awkward option. But it is rather costly for an individual state. However, if a state cooperates with other states having a different flood risk portfolio can reduce the cost of providing this type of insurance. One would expect that the flood risk across European nations is sufficiently diverse such that there is a strong economic incentive for cooperation.

Of course, it is very unlikely that the EU member states would easily agree upon a specific role, the Union could play in (re-)insuring overall national flood risks, given the diversity of approaches being followed in this respect on the national level: Some countries (e.g. Germany, Italy, United Kingdom, and – just recently – Finland) show (purely) market-based systems, sometimes systematically coupled with state-funded ad-hoc relief. Others (e.g. Spain and France) exhibit public or quasi-public monopoly insurance provision. A third group of countries (e.g. Austria, Denmark, Belgium, and non-EU member Norway) manage flood risk transfer either mainly via tax-financed public disaster funds or by means of a combination between public disaster fund and private insurance provision. Due to this diversity - evolved in the light of diverse historical and cultural backgrounds - any harmonization project that seeks to prescribe one solution for all European member states seems a very demanding task, whose usefulness is to be questioned critically. Even discussions within nations on reforming the national systems usually take very long as the examples of Romania, the United Kingdom, Austria, Germany or the Netherlands show (see e.g. Prettenthaler and Albrecher [26]; Surminski [32]; Surminski et al. [31]). This is why the reform option put forward in this paper is of a completely different nature. Instead of harmonizing national legal frameworks it focuses on exploiting the flood risk diversification potential available within the European Union. Once the diversification potential is known, it may well be that bilateral agreements of risk pooling evolve, not necessitating a unanimous stance towards this issue shared by all member states. It is this diversification potential that is illustrated in the following sections and to the calculation of which we now turn.

3 Modelling Flood Risk with EVT Techniques

3.1 Other approaches

Since our modelling method solely focusses on Extreme Value Theory (EVT), it might be a good idea to also give a short overview on other approaches first: Quantitative flood loss modelling has received quite some attention in recent literature (although due to the complexity of the subject flood models are recognized to leave considerable uncertainty, see Merz et al. [21]). Flood losses can be divided into direct and indirect damages, each of which may be further divided into tangible and intangible damages (Merz et al. [22]). The literature on loss modelling has mostly focused on tangible direct damages, since they are easier to quantify than the other kinds of damages. The relative[1] or absolute monetary damage is typically explained by characteristics (factors) of the flood, such as inundation depth, flow velocity, duration of inundation, time of the flood (day/night and season), contamination and flood warning (Merz et al. [22]). In this type of analysis the exposed assets are commonly divided into homogeneous groups (e.g. type of buildings) and for each group the relative (or absolute) damage is described as a function of the considered factors. The main factor is usually inundation depth, leading to the so-called *depth-damage function*, which is derived for a region or a country. For a review of available models see Merz et al. [23]. The following flood models are for instance in this vein:

- FLEMOps (Thieken et al. [35]) for the private sector in Germany. The relative loss is explained by water depth, contamination, building type and quality of the building and is based on the loss data obtained between 2002 and 2006 in the Elbe and Danube catchments in Germany.
- FLEMOcs (Kreibich et al. [16]) for industrial sector in Germany. The relative loss is a function of water depth, contamination, business sector, number of employees and precaution.
- Multi-Coloured Manual (Penning-Rowsell et al. [25]) for the UK, where the absolute loss is explained by water depth, flood duration, building type and age.
- Damage Scanner (see, Jongman et al. [12] for a review) are the standard methods to estimate the flood economic loss based on water depth in the Netherlands.
- A depth-damage function for the special case of dam breach scenarios is provided by Prettenthaler et al. [27].
- The JRC model (Huizinga [10]), which is a pan-European damage model describing absolute monetary loss as a function of water depth. This model is applied by Feyen et al. [7] to evaluate the impact of climate change on fluvial flood risk in Europe.

Jongman et al. [12] applied seven damage estimation models (four of them from the above models) to estimate flood losses of two specific regions and compared estimated to observed values. Results were, however, rather unsatisfactory, which indicates that flood risk modelling efforts need further attention, see also Merz et al. [23].

Due to their 'black-box character' – in the sense that they are not publicly available – the approaches used by commercial risk modelling companies (e.g. AIR, RMS, JBA Risk Management, Ambiental Technical Solutions Ltd., etc.) can unfortunately not be discussed in detail in this paper. However, the field seems to be quite dynamic, with regular releases of new or updated models. Lately, commercial flood risk model providers have also emphasized the importance for (European) insurers to look across national borders and think about the spatial correlations of flood risk across Europe (see e.g. Savina Savina [30]). Whereas RMS, for instance, initially only offered flood risk models for individual countries (including the UK, Belgium and Germany), they

[1] I.e. the monetary value of the damage relative to the total value of the asset

released a pan-Europe flood model encompassing 13 countries in 2015.

The Solvency II Directive of the European Commission within the new regulatory framework for the European insurance industry prescribes capital requirements for insurance companies according to a Value-at-Risk (VaR) at the 99.5% level, i.e. insurance companies are required to hold sufficient capital to remain solvent with a probability of 99.5%. However, linked to the implementation of this rule is the non-trivial task of estimating such extreme quantiles. This is particularly challenging since most often the empirical data available for these estimations are very limited in scope. Clearly, one needs to employ some extrapolation techniques, as in most cases the time interval of available observations does not include such an extreme event. Extreme value theory (EVT) is a natural choice towards that end, see e.g. Beirlant et al. [1]. It provides a tool-kit to model the distribution of extreme events by using patterns of the largest observations. In particular, it is a sensible way to describe tails of a distribution based on smaller observations, and hence provides a reasonable way to extrapolate data sets beyond their range, something that is needed to calculate the VaRs. In this paper we will apply EVT methodology to model the tail of the distribution of flood risks, for individual European countries and for Europe as a whole. In particular, in view of the Solvency II guidelines, we aim to establish estimates on the VaR at the 99.5% level on the basis of historical loss data, considering also the change of the building stock (value) over the years. Whereas in insurance practice, flood risk may eventually be pooled with other risks, and the VaR reported to the regulator will include a number of further factors such as the assets of the company, loss reserves etc., the specification of the stand-alone VaR figure is a natural indicator for the underlying flood-specific risks of each country, indicating the potential and *likely* exposure.

3.2 Methods

Flood loss data often exhibit a heavy tail, with the largest observed values typically dominating the others substantially. Heavy-tailed distributions often provide reasonable fits in such contexts. Popular heavy-tailed distributions are the log-normal distribution with cumulative distribution function (cdf)

$$F_Y(y) = \Phi\Big(\frac{\log y - \mu}{\sigma}\Big), \quad y > 0 \tag{1}$$

(where Φ is the cdf of a standard normal distribution), the Weibull distribution with cdf

$$F_Y(y) = 1 - \exp[(-y/\tau)^{\alpha}], \quad y > 0, \tag{2}$$

with parameters $\tau > 0$ and $\alpha > 0$ (where the heavy-tailed case $0 < \alpha < 1$ is of prime interest in the present context), and the classical Pareto distribution with two parameters $\alpha, \theta > 0$, which assigns a power decay for the tail

$$F_Y(y) = 1 - (\theta/y)^{\alpha}, y \geq \theta, \tag{3}$$

and often provides a very reasonable fit for large losses. Whereas these two distributions result from a simple transformation of a normal and exponential, respectively, random variable (which may be considered as a sufficient justification of its choice, looking for compromise between simplicity, clarity and flexibility of models), the Pareto distribution in addition appears naturally as a limit distribution for maxima of samples (see e.g. [1]). As one is mainly concerned with the tail of the fitted distribution, this link also gives guidelines on how to fit such a distribution only to the larger values among all observations. Despite the fact that the shape of much of the distribution tail may be well described by such a model, there may be many situations in practice, for which there is a natural upper bound for loss random variables (such as the overall property value in flood prone areas). In a recent paper, Beirlant et al. [2] adapt classical EVT techniques to fitting procedures for such a truncated Pareto model, where (3) is adapted to

$$F_Y(y) = \frac{1-(\theta/y)^\alpha}{1-(\theta/T)^\alpha}, \quad \theta \le y \le T. \tag{4}$$

The upper bound T will typically not be known, but can be estimated from the data. One can then also compare the goodness of fit of various models (with and without truncation) and choose the one that is most plausible for the given data situation.

In this paper we apply such an analysis to annual flood loss data for residential buildings, aggregated per country for 27 European Union countries.[2] Out of these 27 countries, 7 countries have less than 5 data points, which we consider to be not sufficient to see enough statistical structure in the data to include them in the analysis. In addition, we also exclude the Netherlands since due to extensive protection levels by dams and dikes, the nature of losses is quite different from those of other countries.[3] Hence we restrict ourselves to 19 countries. The last year of reported annual losses for all countries is 2013, but the first year differs from country to country. For each of the 19 countries[4] considered within the analysis, Table 1 depicts the first year of reported loss, the total number of years comprised by the record and the number of years with a loss occurring. The maximum amount of losses for each country is included in Table 2. For each country and year, we normalize the loss data by the overall residential building value. Both damage data and building values are inflation adjusted.

For the fitting of the Pareto and truncated Pareto distribution, we apply the method of Beirlant et al. [2], which is an adaptation of the classical Hill estimator. This method works remarkably well on simulated data with truncation, and in the limit of the truncation parameter T going to ∞, the procedure retains the classical EVT Hill estimator for α . Note that if the largest k data points are used for the estimation, the parameter θ is naturally chosen to be the smallest of these used values. There are various suggestions and algorithms available in the literature towards a suitable choice of k. Here we adopt a covariance criterion (as suggested in Beirlant et al. [2]).

The parameters of the log-normal and Weibull distributions are estimated by using classical maximum likelihood estimation. We use Q-Q plots to compare the quality

[2]We gratefully acknowledge Munich Re for providing data from their loss database NatCatSERVICE (Munich Re [29]).

[3]The overall insurability of flood risk in the Netherlands with large parts of the country below sea level is in any case a general subject of debate. That is, why insurance cover is almost non-existent in the Netherlands (see e.g. Seifert et al. [32]).

[4]AT: Austria, BE: Belgium, BG: Bulgaria, HR: Croatia, CY: Cyprus, CZ: Czech Republic, FR: France, DE: Germany, GR: Greece, HU: Hungary, IE: Ireland, IT: Italy, PL: Poland, PT: Portugal, RO: Romania, SK: Slovakia, ES: Spain, SE: Sweden, UK: United Kingdom.

	AT	BE	BG	HR	CY	CZ	FR	DE	GR	HU
First year	1980	1991	1991	1999	1992	1993	1980	1980	1982	1996
# Data	34	23	23	15	22	21	34	34	32	18
# Loss > 0	24	11	11	7	6	14	30	32	18	12
	IE	IT	PL	PT	RO	SK	ES	SE	UK	
First year	1990	1980	1991	1980	1992	1997	1980	1985	1980	
# Data	24	34	23	34	22	17	34	29	34	
# Loss > 0	16	31	17	15	19	11	32	9	32	

Table 1: First year, number of years with data and number of years with losses, per country

of fits among each other and on the basis of those (together with empirical mean-excess plots and related methods) decide for the most suitable among the different models for each country. Clearly, there is a certain degree of subjectivity in the corresponding choice, but in view of the small number of available data points one cannot use classical goodness-of-fit tests (like a χ^2-test), which is a well-known artifact in EVT. The procedure adopted here seems to be a reasonable compromise between scientific rigor, intuition and experience when working with this kind of data. For illustration, Figure 1 depicts the log-log plot

$$(\log X_{n-j+1,n}, \log(j/n)), \quad j = 1, \ldots, n, \tag{5}$$

for those countries which pass the test for a truncated Pareto distribution given in Beirlant et al. [2]. One clearly sees the deviation from the (linear) non-truncated Pareto pattern at the right-hand end of the plots.

3.3 Fitted Models and Risk Measures

Figure 2 depicts the Q-Q plots as a measure of goodness of fit for each candidate distribution and each country (in those cases where the truncated Pareto assumption is rejected, we do not give the respective Q-Q plot, as then no estimate for the upper bound is available). From these plots, we choose the most suitable model for each country. For Croatia the fit is not very satisfactory (possibly due to insufficient data), we still include it in the analysis, but give a word of caution to the respective numbers. Given that insurance solutions should account also for a massive failure of dams, a high protection level by dams should be treated separately. Here the given numbers do certainly not reflect the risk under a major 'failure of dams' scenario. For Europe we aggregated the annual losses over all countries and then applied the same fitting procedure as for the individual countries.
For determining the VaR (i.e. the quantile) at the 99.5% level, which is a quantity relevant for solvency purposes, there is a simple procedure in the present case: if only data points larger than θ are finally used for the estimation of the tail, and a conditional distribution F_Y is chosen to be the best model above that level θ, that is

$$\mathbb{P}\{Y \geq y | Y \geq \theta\} = 1 - F_Y(y), \tag{6}$$

it follows that

$$\mathbb{P}(Y \geq y) = \zeta_\theta(1 - F_Y(y)) := 1 - \beta,$$

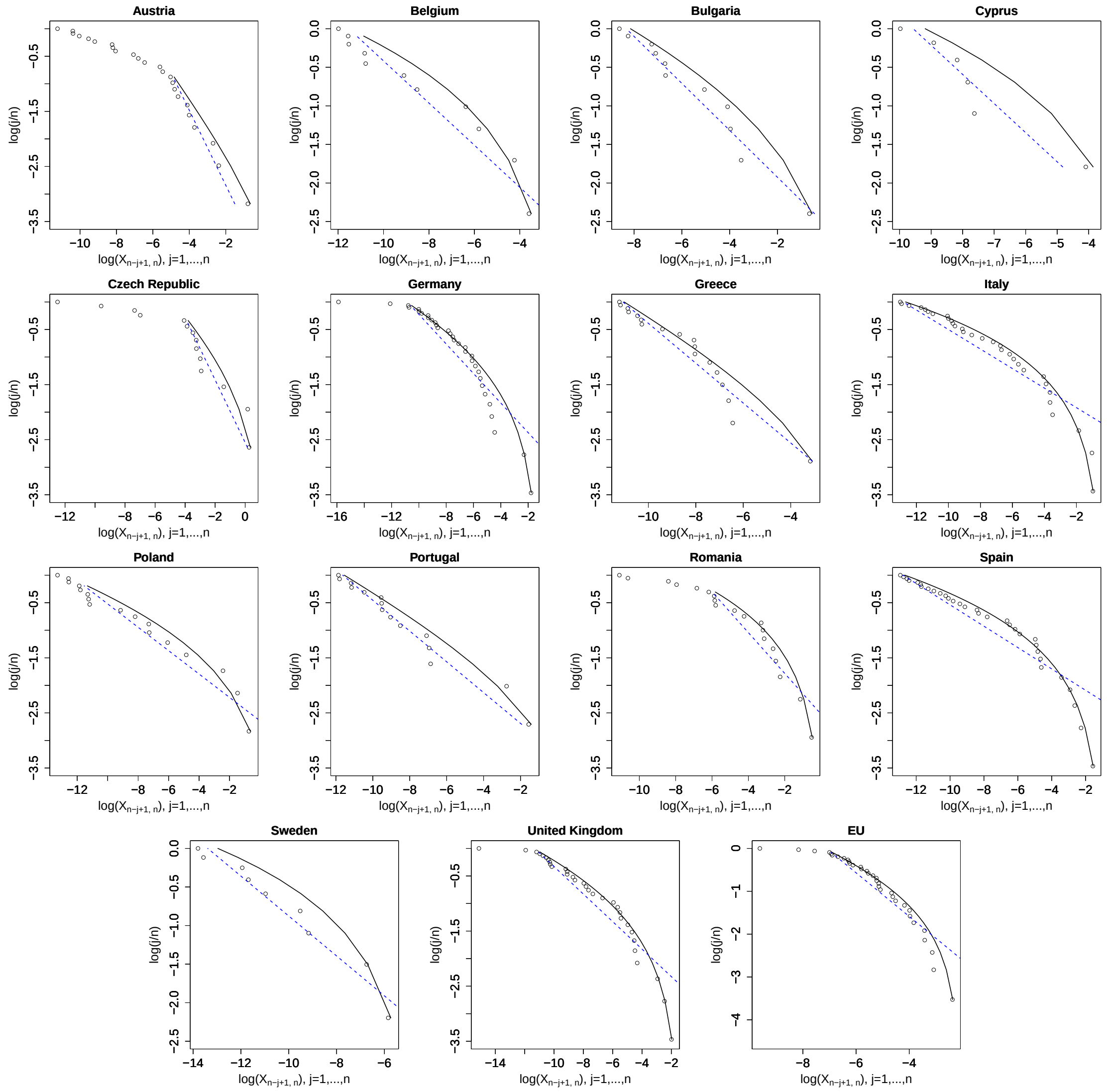

Figure 1: Log-log plots for annual flood loss data by country. The dashed blue line refers to a Pareto fit, whereas the solid black line refers to a truncated Pareto fit.

where $\zeta_\theta = \mathbb{P}(Y > \theta)$ can be estimated by k/n (here k is the number of used observations and n is the size of the entire sample) and β is the level at which the VaR is calculated. For a chosen value of β (0.995 in the present case), the VaR is then the implicit solution of the above equation for y.
In recent years several alternatives to VaR as a risk measure have been proposed. The most prominent alternative is *expected shortfall* at confidence level β

$$\mathrm{ES}_\beta(Y) = \mathbb{E}(Y | Y \geq \mathrm{VaR}_\beta(Y)) \tag{7}$$

This risk measure is e.g. implemented in the Swiss Solvency Test for $\beta = 0.99$. It has some desirable properties, and even if most European countries due to regulatory rules adhere to the VaR, we give here also the respective ES numbers for comparison.

Table 2 depicts for each country the chosen distribution, the largest observed insurance loss (both in absolute terms and in % of the building value) and the fitted upper bound T (in case the truncated Pareto distribution is the best model). The fifth column gives the building values of 2013, whereas the last four columns present the resulting VaR (99.5 %) and ES (99%) in terms of percentage of 2013 building values as well as in absolute value, in addition, the value at risk and expected shortfall for all mentioned distributions have been showed in Appendix. One sees that for some countries the ES is considerably higher than the respective VaR, particularly for those countries where the log-normal distribution is the best fit. Figure 3 depicts the relative value of the resulting VaR for each country, indicating which countries are most prone to flood risk, given the data analysed.

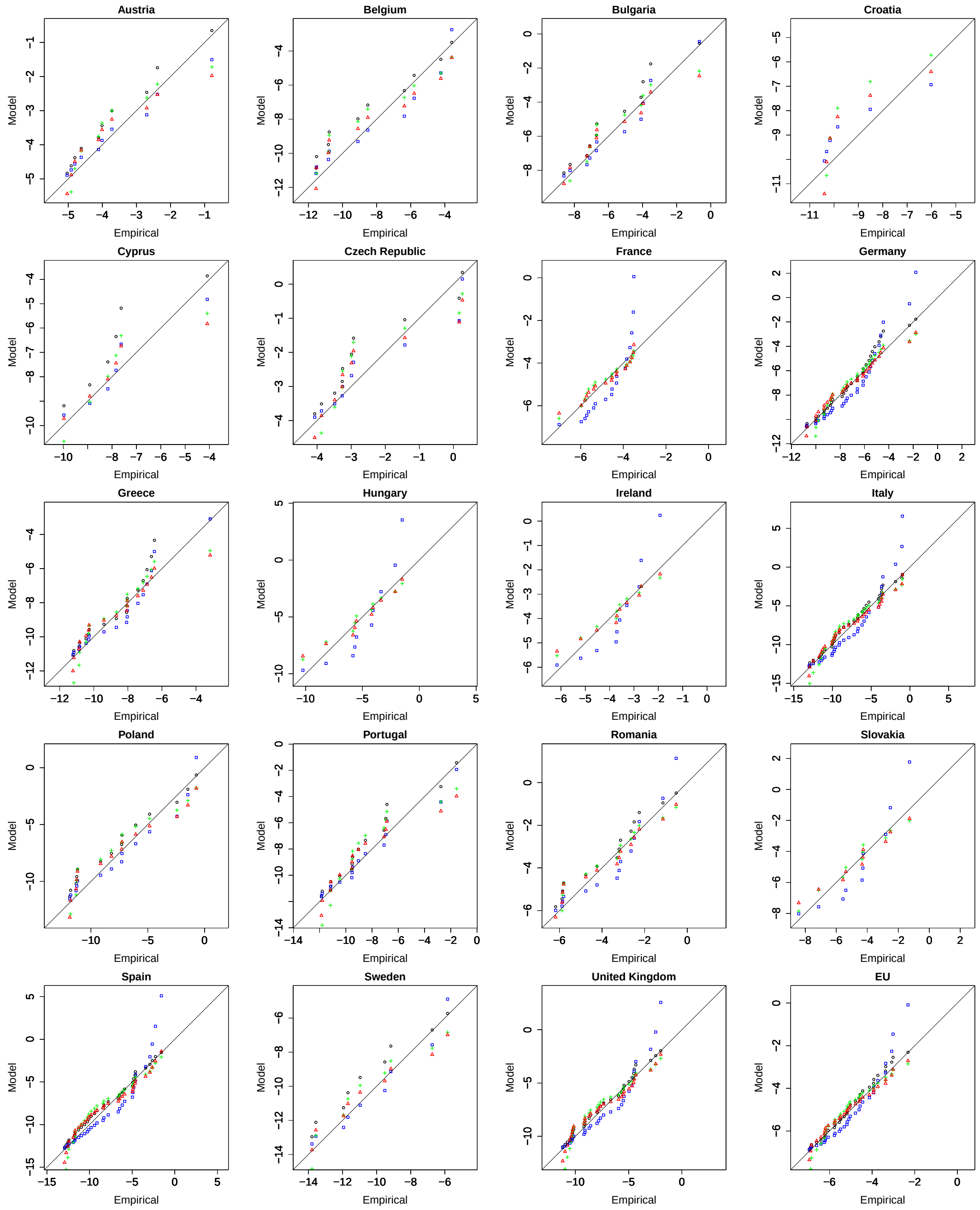

Figure 2: QQ-plots for annual flood loss data (in logarithmic scale) by country. The black circles, blue squares, red triangles and green pluses respectively refer to a truncated Pareto, Pareto, log-normal and Weiblull fit.

4 Joint Risk Pooling: A thought experiment

The sum of the VaRs of the individual countries in Table 2 represents the overall capital amount that would be needed at the 99.5% safety level in case each country dealt with flood risks stand-alone. With 141,052 Mio € it is almost

		Largest Obs.		T(TP)	BV-2013	VaR(99.5%)		ES(99%)	
Country	Dist.	% BV	Mio €	% BV	Mio €	% BV	Mio €	% BV	Mio €
Austria	TP	0.455	3,970	5.167	914,593	2.53	23,139	3.22	29,460
Belgium	TP	0.027	211	0.086	792,452	0.074	586	0.081	644
Bulgaria	TP	0.514	773	2.464	141,053	1.983	2,797	2.22	3,134
Croatia	LN	0.079	158	Inf	197,198	0.122	241	0.66	1,309
Cyprus	TP	0.017	6	0.098	40,062	0.076	30	0.091	36
Czech R.	TP	1.3	4,080	3.644	323,412	3.181	10,288	3.33	10,779
France	LN	0.03	1,660	Inf	6,001,039	0.051	3,078	0.106	6,396
Germany	TP	0.167	14,900	0.286	8,704,763	0.26	22,632	0.264	23,000
Greece	TP	0.042	208	0.279	511,834	0.189	967	0.225	1,153
Hungary	LN	0.223	673	Inf	291,411	2.231	6,501	6.9	20,138
Ireland	LN	0.145	410	Inf	286,464	0.322	922	0.475	1,363
Italy	TP	0.391	12,203	0.621	3,366,374	0.57	19,188	0.576	19,399
Poland	TP	0.483	5,160	2.186	1,065,883	1.794	19,122	1.89	20,202
Portugal	TP	0.21	1,090	4.012	513,923	2.084	10,710	3	15,415
Romania	TP	0.594	1,690	0.985	266,283	0.927	2,468	0.935	2,491
Slovakia	LN	0.28	490	Inf	175,723	1.2	2108	2.75	4830
Spain	TP	0.209	3,670	0.343	2,161,979	0.314	6,798	0.316	6,827
Sweden	TP	0.003	32	0.009	1,175,719	0.007	82	0.008	97
United K.	TP	0.137	6,000	0.224	4,583,064	0.205	9,395	0.207	9,492
Sum							141,052		176,165
Europe	TP	0.093	29,842	0.131	31,513,229	0.122	38,446	0.123	38,761

Table 2: Chosen model, largest observed insurance loss, fitted upper bound T, total building value 2013, 99.5 % VaR and 99% ES for 19 EU member states and their aggregate

four times as large as the VaR calculated on the basis of the aggregated loss data of all 19 member states (referred to as "Europe" in Table 2), which incorporates the dependence structure between the individual countries. In other words, pooling the flood risk across these 19 EU member states reduces the capital requirements[5] to 38,446 Mio €. Hence, there is a strong diversification potential for pooling flood risk across countries. Based on this observation, the implementation of a flood damage pool or a joint reinsurance either at EU level, or – if no agreement at EU level could be achieved – between subsets of EU countries, seems a reform option worthwhile to consider. Given the available data set and based on our model assumptions, we can hence identify the most effective *Joint Risk Pooling Initiatives* (JRPIs) in terms of reducing solvency capital requirements.

To that end, we divide the 19 EU member states into two groups. The first group has a rather satisfactory data base available (correspondingly the goodness-of-fit of the calibrated models is quite satisfactory) and constitutes the countries with larger losses (in fact about 80% of the over-all reported losses in the data set, and – coincidentally – also about 80% of the total building values are located in these countries). This group includes the seven countries Austria, France, Germany, Italy, Portugal, Spain and United Kingdom. The

[5]The VaR figures reported to the regulator will typically substantially differ from the stand-alone VaR figures of 2, since flood risk is often pooled with other risks and further factors are relevant (assets of the company, loss reserves, etc. will be considered).

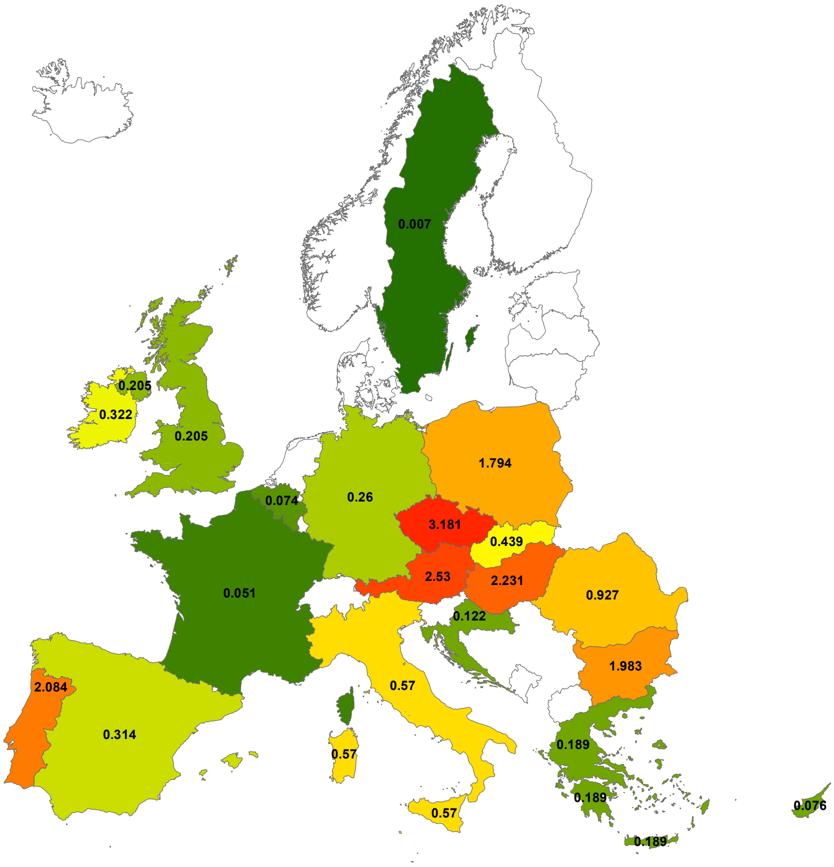

Figure 3: Relative value of the 99.5%-VaR, per country

second group consists of the remaining 12 countries, for which there are fewer data points available, but also flood risk is less prominent.

For the pooling of countries of Group 1, denote by $X_1, X_2, \dots, X_7$ the random variables representing losses of these seven countries. The goal is now to find the number of clusters G (and the number N_g of member countries in cluster g) which minimizes the sum of VaRs of the G clusters:

$$\mathrm{VaR}_G = \min \sum_{i=1}^{G} \mathrm{VaR}\Big(\sum_{j \in N_g} X_j \Big) \tag{8}$$

For each cluster, we aggregate the loss data of the N_g countries, fit a truncated Pareto distribution to these and compute the respective VaR (with the exception of France, the truncated Pareto was the best model for these countries anyway). Doing this analysis for all possible combinations of two and three clusters, we can identify the optimal clusters. Tables 3 and 4 show the countries and VaR figures of the resulting clusters. In the last two columns we also give the corresponding numbers when ES is used as the risk measure.

For pooling of the remaining 12 countries (Group 2), the available data situa-

Cluster	Countries	VaR(99.5%)		ES(99%)	
		Individual	Cluster	Individual	Cluster
1	Austria	23,139	6,893	29,460	6,987
	France	3,078		6,396	
	Portugal	10,710		15,415	
2	Germany	22,632	26,165	23,000	26,184
	Italy	19,188		19,399	
	Spain	6,798		6,827	
	UK	9,395		9,492	
Sum		94,940	33,148	110,026	33,171

Table 3: VaR and ES values of two clusters

Cluster	Countries	VaR(99.5%)		ES(99%)	
		Individual	Cluster	Individual	Cluster
1	Austria	23,139	7,966	29,460	7,967
	UK	9,395		9,492	
2	Portugal	10,710	6,607	15415	6,407
	Spain	6,798		6827	
3	France	3,078	27,827	6,396	27,827
	Germany	22,632		23,000	
	Italy	19,188		19,399	
Sum		94,940	42,400	110,026	42,401

Table 4: VaR and ES values of three clusters

tion does not allow to proceed in the same way as for Group 1, because there are not enough joint data points available for losses in the same years. One can instead use a hierarchical clustering algorithm (see e.g. Kaufman and Rousseeuw [14]). In general, clustering by such an algorithm is based on a certain measure of distance between the clustering objects, with the goal to minimize the distance within and maximize the distance between clusters. In the present context, this distance can be the pairwise correlation, so that each cluster consists of the countries that are the least correlated with each other, in view of diversification benefits. To determine the pairwise correlation between losses of the countries, one can e.g. use the classical Pearson correlation

$$r_P = \frac{(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2}\sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}},$$

or the Spearman rank correlation

$$r_S = \frac{(rg(x_i) - \overline{rg}_x)(rg(y_i) - \overline{rg}_y)}{\sqrt{\sum_{i=1}^n (rg(x_i) - \overline{rg}_x)^2}\sqrt{\sum_{i=1}^n (y_i - \overline{rg}_y)^2}},$$

where $(x_1, y_1), \ldots, (x_n, y_n)$ are the joint observations of n flood losses, and $rg(x_i)$ is the rank of observation x_i in the univariate sample. Recall that the Spearman rank correlation is the Pearson correlation coefficient of the grades of the distribution, and in that way measures for monotonic relationships between two random variables, whereas the Pearson correlation coefficient itself measures linear correlation only. Linear correlation is a very natural concept in the world of normal distributions, but in the present context, the marginal random variables are strongly skewed and heavy-tailed so that the Spearman correlation may be seen as a more natural choice (see e.g. Embrechts et al. [6]). Correspondingly we use it here. Table 5 shows the pairwise Spearman correlation of countries in Group 2. When deciding for three clusters according to the clustering algorithm described above, they turn out to be

1. Croatia and Czech Republic
2. Bulgaria, Greece, Ireland and Romania
3. Belgium, Cyprus, Hungary, Poland, Slovakia and Sweden.

If one only allows for two clusters of countries, the first cluster is as above and the second cluster is the aggregation of the second and third cluster above.

	BE	BG	HR	CY	CZ	GR	HU	IE	PL	RO	SK	SE
BE	1	-0.27	0.05	-0.85	-0.20	-0.10	-0.30	-0.21	-0.16	-0.11	-0.25	-0.63
BG		1	0.14	-0.43	-0.38	-0.19	0.21	-0.73	0.15	0.30	0.17	-0.55
HR			1	-0.55	-0.34	0.37	-0.13	-0.52	0.33	0.11	0.37	-0.10
CY				1	-0.11	-0.31	-0.47	-0.63	-0.56	-0.45	-0.58	-0.77
CZ					1	0.26	0.03	0.06	0.20	0.05	-0.05	-0.18
GR						1	-0.05	-0.19	0.20	0.22	0.26	-0.10
HU							1	-0.38	0.04	0.36	0.08	-0.44
IE								1	-0.34	-0.47	-0.68	0.15
PL									1	0.49	0.60	-0.01
RO										1	0.57	0.06
SK											1	-0.19
SE												1

Table 5: Pairwise Spearman correlation for relative losses of countries in Group 2

Having identified reasonable clusters on the basis of bivariate correlations, it would now be the next step to calculate VaR figures for the resulting clusters. However, the scarce data situation for the countries of Group 2 does not allow for reasonable estimates on quantiles of each cluster. For fitting a distribution to the aggregated losses of a cluster, only data from those years covered by the loss record of every country in the cluster can be used. Unfortunately this reduces the number of available summed claims too much to provide meaningful fits for their distribution (and then estimate a 99.5% VaR), and we hence restrict ourselves at this point to simply outlining the clusters as given above. In addition we remind the even more severe data limitation for Croatia.

Remark. Tables 2, 3 and 4 indicate that under suitable collaboration between countries, diversification can significantly reduce the total required solvency capital for flood insurance. Such numbers bring up the question on how such a reduced aggregate capital requirement should then be subdivided ("allocated") to the individual countries. In the literature some suggestions for that have been developed, among them the Euler allocation principle, see e.g. Tasche [34]. In order to implement such an allocation procedure, one needs to fully specify a dependence model for the multivariate loss distribution across countries. However, due to the limited amount of available data, we do not pursue the formulation of such a concrete dependence model in the present paper, as our focus is on the aggregate view. Clearly, with a more refined data set available, it will be interesting to elaborate further on such aspects in the future.

5 Conclusion

In this paper we discussed some challenges in flood risk assessment and management for Europe. High spatial correlation of flood damages is one of the obstacles for a well-functioning flood insurance scheme on the national level. However, understanding the dependence structure across national flood damage data, (non-)correlation can become part of the solution to provide flood insurance for Europe: Based on a data set comprising annual flood losses of most EU member states, we calibrated flood models using a methodology for truncated distributions developed recently in extreme value theory. The resulting models provided a tool to quantify flood risk diversification potentials. Based on the results, our suggestion is to exploit Europe's magnitude and diversity related to flood risk by jointly buying reinsurance or forming a risk pool. In case a collaboration on the entire EU level is not feasible, the voluntary establishment of Joint Risk Pooling Initiatives (JRPIs) between subsets of EU countries seems an option worthwhile to consider. In the paper at hand we not only created the methodological framework to actually quantify concrete diversification benefits of such JRPIs, but also did some explicit calculations where feasible for the data. The results presented in the paper are clearly subject to and limited to the quality of the available data, and it will be an interesting challenge to deepen the analysis in the future with improved and enlarged data sets. E.g., to our knowledge smaller countries that have a strong national reinsurance tradition may be under-represented in the utilized data set (stemming from an international reinsurer), thus some more data gathering activities might be a valuable undertaking from an EU-wide perspective.

For our analysis, the question who actually takes the responsibility to insure a nation's flood risk is not relevant. How deeply the state government should be involved in risk transfer also may be a matter of taste and economic policy doctrines. What our analysis clearly shows, however, is that European flood risk is diversified in a way such that there are strong economic incentives to pool the national risk portfolios. What also becomes clear from the analysis is that once some role of public governance for a functioning risk transfer mechanism for flood risk is accepted, the question of sound (damage) data provision and publicly available risk models based on such sound data also becomes a key requisite for providing cheap and sound insurance solutions.

6 Appendix

In the following Tables 6 and 7, we list for completeness the resulting VaR and ES for all distributions that were discussed in this paper. Note that some of these distributions did not provide a good fit (see Figure 2) and are not advised to be eventually used (that is why we identified the best fit among the four distributions for each case), but the numbers allow to assess the sensitivity of the resulting capital requirements on the underlying distribution used in the model. As can be seen, the consequences can be dramatic in terms of magnitude. Naturally, the more data there are available, the more reliable a suggestion can be given on which class of distributions would fit best. One observation that becomes very clear from the figures in Tables 6 and 7 is how crucially the assumption of a truncated Pareto (instead of a non-truncated Pareto) influences the conclusions. Note that for the non-truncated Pareto distribution fit, the resulting estimate of α turns out to be smaller than 1 for all countries, so that the expected shortfall in that case is infinite.

	BV-2013	Pareto		T. Pareto		Log-Normal		Weibull	
	Mio €	% BV	Mio €	% BV	Mio €	% BV	Mio €	% BV	Mio €
Austria	914'593	2.2	2.1×10^4	2.530	23'136	0.362	3'313	0.377	3'446
Belgium	792'452	8.4×10^1	6.7×10^5	0.075	594	0.164	1'300	0.066	522
Bulgaria	141'053	4.3×10^2	6.0×10^5	1.983	2'797	0.649	915	0.478	675
Croatia	197'198	1.7	3.4×10^3	-	-	0.123	242	0.122	240
Cyprus	40'062	1.1	4.6×10^2	0.076	30	0.017	7	0.019	8
Czech R.	323'412	4.3×10^1	1.4×10^5	3.181	10'289	2.558	8'272	2.087	6'750
France	6'001'039	5.7×10^1	3.4×10^6	-	-	0.087	5'220	0.047	2'803
Germany	8'704'763	4.6×10^3	4.0×10^8	0.262	22'829	0.264	22'965	0.130	11'335
Greece	511'834	5.3	2.7×10^4	0.189	967	0.025	128	0.021	108
Hungary	291'411	1.1×10^7	3.2×10^{10}	-	-	2.231	6'503	0.487	1'420
Ireland	286'464	2.1×10^2	6.1×10^5	-	-	0.322	923	0.174	498
Italy	3'366'374	1.1×10^7	3.7×10^{11}	0.570	19'183	3.712	124'974	0.820	27'608
Poland	1'065'883	3.3×10^4	3.5×10^8	1.794	19'120	4.365	46'531	1.393	14'853
Portugal	513'923	5.7×10^1	2.9×10^5	2.084	10'712	0.164	845	0.168	861
Romania	266'283	8.3×10^2	2.2×10^6	0.927	2'469	1.708	4'549	0.800	2'131
Slovakia	175'723	8.9×10^4	1.6×10^8	-	-	1.204	2'116	0.440	774
Spain	2'161'979	1.1×10^6	2.4×10^{10}	0.314	6'783	2.442	52'786	0.461	9'971
Sweden	1'175'719	5.5	6.5×10^4	0.007	85	0.008	92	0.005	53
United K.	4'583'064	1.2×10^4	5.5×10^8	0.205	9'410	0.607	27'837	0.196	9'002
EU	31'513'229	2.7×10^1	8.5×10^6	0.122	38'446	0.154	48'530	0.095	29'938

Table 6: Relative and absolute Value-at-risk at 99.5% level for all discussed marginal distributions

	BV-2013	Pareto		T. Pareto		Log-Normal		Weibull	
	Mio €	% BV	Mio €	% BV	Mio €	% BV	Mio €	% BV	Mio €
Austria	914,593	-	-	2.784	25,462	0.477	4,359	0.427	3,903
Belgium	792,452	-	-	0.075	596	0.544	4,307	0.089	703
Bulgaria	141,053	-	-	1.998	2,818	1.291	1,821	0.605	853
Croatia	197,198	-	-	-	-	0.348	687	0.176	347
Cyprus	40,062	-	-	0.077	31	0.028	11	0.023	9
Czech R.	323,412	-	-	3.196	10,336	3.562	11,521	2.374	7,679
France	6,001,039	-	-	-	-	0.102	6,117	0.049	2,944
Germany	8,704,763	-	-	0.263	22,890	0.497	43,229	0.159	13,834
Greece	511,834	-	-	0.194	995	0.043	220	0.026	133
Hungary	291,411	-	-	-	-	5.232	15,247	0.584	1,703
Ireland	286,464	-	-	-	-	0.402	1,152	0.187	535
Italy	3,366,374	-	-	0.572	19,255	16.133	543,089	1.158	38,995
Poland	1,065,883	-	-	1.801	19,202	32.575	347,211	2.223	23,700
Portugal	513,923	-	-	2.249	11,557	0.612	3,143	0.257	1,322
Romania	266,283	-	-	0.928	2,472	2.513	6,693	0.903	2,406
Slovakia	175,723	-	-	-	-	2.037	3,580	0.510	896
Spain	2,161,979	-	-	0.314	6,791	9.835	212,631	0.643	13,899
Sweden	1,175,719	-	-	0.007	86	0.022	264	0.006	72
United K.	4,583,064	-	-	0.206	9,428	1.417	64,946	0.248	11,365
EU	31,513,229	-	-	0.122	38,289	0.189	59,560	0.102	32,143

Table 7: Relative and absolute Expected Shortfall at 99% level for all discussed marginal distributions

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