Insurability of Critical Infrastructures

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1 Introduction

The business model of an insurance company is centered around the idea of risk assessment and control. Insurance is a mechanism that transfers risk from the policy holder to the insurance company for the cost of a predefined premium [16]. The firm must minimize any volatility that comes with this risk in order to minimize the probability of bankruptcy. If the risk event can be observed often, the firm can use the law of large numbers to achieve this goal. This statistical theorem states that the average outcome of large numbers of independent trials is close to the expected value [4]. Therefore, by holding a large number of individual and independent policies of the same line of business (e.g. motor and life insurance) in a portfolio, the insurance company can reduce volatility and does, on average, not expect any large deviations from the calculated mean [16, 21].

Specialized work in extremal risk and damage management illustrates that coverage can be provided as long as the risk is observable and occurs at random [7, 10]. Therefore, insurance for large-scale weather-related damage and even natural disaster exists, as exemplified by Table 1 [29]. The capability of an insurance

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Table 1 Examples of insurance coverage for extreme events

Year	Major disaster	Insured loss [m USD]	Total loss [m USD]
1992	Hurricane Andrew (US)	51,875.1	105,310.4
1994	Northridge Earthquake (US)	45,083.6	159,894.7
1999	Winter Storm Lothar (EU)	51,929.8	165,498.7
2001	9/11 Attacks (US)	53,369.5	200,043.0
2005	Hurricane Katrina, Rita, Wilma (US)	139,741.1	313,045.9
2010	Chile & New Zealand Earthquakes	58,640.6	263,860.5
2011	Japan & New Zealand Earthquakes, Thailand flood	142,728.4	454,402.0
2012	Hurricane Sandy (US)	78,748.3	200,382.3
2015	Earthquake in Nepal (NP)	39,437.9	99,317.7
2017	Hurricanes Harvey, Irma, Maria (US)	150,089.9	349,580.5
2018	Camp Fire (US), Typhoon Jebi (JP)	84,669.9	164,986.1

firm to sustain such large payouts for extremal damage is further strengthened by geographic or business segment diversification [14] and reinsurance. While the expected payout is identical whether or not the firm purchases reinsurance, volatility is significantly reduced as the risk is partially transferred to the reinsurer. This effect also reduces the insolvency risk of the firm [6, 9].

However, natural disaster risk is essentially probabilistic, i.e. such disasters occur at random, and they can be predicted from past observed events.

Weather-related and seismic movements are monitored by many institutions on a global scale. The data and predictions these researchers generate are not publicly available, but they also inform the catastrophe modeling software that is widely used in the insurance industry.

However, information about intentional attacks on infrastructure is often kept secret or only shared in non-public industry expert groups. This implies it is difficult to specify a probability distribution of extreme events because the low number of observations biases estimators. Most importantly, intentional attacks do not change at random like the weather does, on the contrary, their strength and effectiveness grows as attackers learn about the architecture of the infrastructure. The attack pattern may also change as the attacker's resource endowment changes. As a result, intentional attacks are essentially random, such that it is almost impossible to build a probabilistic model for intentional attacks.

Our analysis begins with a sample of documented intentional attacks on infrastructures and the financial damage inflicted by these attacks [3]. Table 2, documents the 20 most costly terrorist acts of the past decades. We fit a Pareto distribution to these data, proposing a method to generate unbiased estimators for its auxiliary parameters (Sect. 2). In a second step, we adapt a compartmentalized model to our context, infusing it with the above estimators to simulate a private insurance firm's accumulated net profit and loss over time (Sect. 3). Our results suggest that it is highly unlikely that such a firm would ever offer coverage for intentional attacks on infrastructure, and we provide some discussion of potential alternatives (Sect. 4).

Table 2 The 20 worst terrorist acts—insured property loss in 2017 USD

Event	Date	Location	Insured property loss [m USD]	Fatalities
9/11 Attacks	09.11.2001	New York, Washington DC	26,215	2982
Bomb in financial district	24.04.1993	London	1276	1
IRA bombing	15.06.1996	Manchester	1038	0
Bomb in financial district	10.04.1992	London	937	3
Bomb in World Trade Center	26.02.1996	New York	872	6
Rebels destroy military and civilian aircrafts	24.07.2001	Colombo	555	20
IRA bombing	09.02.1996	London	361	2
Bombing on board of a 747	23.06.1985	North Atlantic	227	329
Truck bomb	19.04.1995	Oklahoma City	203	166
Hijacked Swissair/BOAC dynamited on ground	12.09.1970	Jordan	178	0
Hijacked PanAm dynamited on ground	06.09.1970	Cairo	154	0
Bomb in financial district	12.04.1992	London	134	0
Attack on two hotels	26.11.2008	Mumbai	117	172
Bomb attack on a prison	27.03.1993	Weiterstadt	99	0
Bomb at Barajas airport	30.12.2006	Madrid	82	2
Bomb on board of a PanAm	21.12.1988	Lockerbie	80	270
Riot	25.07.1983	Sri Lanka	65	0
Bombing in a tube and a bus	07.07.2005	London	65	52
Hijacked airplane ditched at sea	23.11.1996	Indian Ocean	62	127
Bomb attack on Israel's embassy	17.03.1992	Buenos Aires	53	24

2 Pareto Estimation of Risk Premiums

Using a Pareto distribution (*PA*) is advantageous whenever a limited sample of observations on extreme events is to be analyzed [17]. Specified by a scale parameter ($x_0 > 0$) that captures minimum loss and a shape parameter ($\alpha > 0$) that determines curvature and tails, its distribution function for a continuous random variable X is given by Quandt [24].

$$F_X(x, \alpha) = \mathbb{P}(X \leq x) = \begin{cases} 1 - \left(\frac{x_0}{x}\right)^{\alpha} & \text{if } x \geq x_0 \\ 0 & \text{else} \end{cases} \tag{1}$$

Since we are using the discrete sample data in Table 2 to estimate x_0 and α, we can exploit the fact that the distribution functioncan be rewritten as follows for a discrete random variable X, where n corresponds to the number of observations in the dataset [28]:

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} \mathbf{1}_{X_i \le x} \text{ with } \mathbf{1}_{X_i \le x} = \begin{cases} 1 \text{ if } X_i \le x \\ 0 \text{ else} \end{cases} \tag{2}$$

Applying (2) to the observations in Table 2, $F_n(x)$ can be determined and plotted once maximum likelihood estimators for x_0 and α are available. Since the losses in Table 2 are numerically large, the estimator for x_0 is simply given by

$$\hat{x_0} = \min_{i \in [1,n]} X_i \tag{3}$$

Hence, $\hat{x_0} = 53$ m USD. The specification of an estimator for α is more complex since it requires a likelihood function [24, 27] which we specify as

$$\mathfrak{L}(X_i, \alpha) = \prod_{i=1}^{n} \frac{\alpha^n x_0^{\alpha n}}{X_i^{(1+\alpha)}} \tag{4}$$

Logging this function and calculating partial derivatives yields

$$\frac{\partial \ln(\mathfrak{L}(X_i, \alpha))}{\partial \alpha} = \frac{n}{\alpha} + n\ln(x_0) - \sum_{i=1}^{n} \ln(X_i) = 0 \tag{5}$$

which, after isolation of α, gives the estimator

$$\hat{\alpha} = \frac{n}{\sum_{i=1}^{n} \ln\left(\frac{X_i}{x_0}\right)} \tag{6}$$

$\hat{\alpha}$ is a biased estimator that requires transformation such that a minimum-variance consistent unbiased estimator can be obtained. Since $\ln\left(\frac{X_i}{x_0}\right)$ follows an exponential distribution, the consistent estimator $\tilde{\alpha}$ is

$$\tilde{\alpha} = \frac{n-1}{\sum_{i=1}^{n} \ln\left(\frac{X_i}{x_0}\right)} \tag{7}$$

Now that we have obtained estimators for both the scale and the shape parameter, the Pareto distribution specified by these is fitted to the data in Table 2. We obtained an initial estimate of $\tilde{\alpha} = 0.6143$. To improve the accuracy of $\tilde{\alpha}$, following [15] we used the method of least squares to minimize the deviation between measured and predicted values $S(\alpha)$:

$$S(\alpha) = \sum_{i=1}^{n} (F_n(X_i) - F(X_i, \alpha))^2 \tag{8}$$

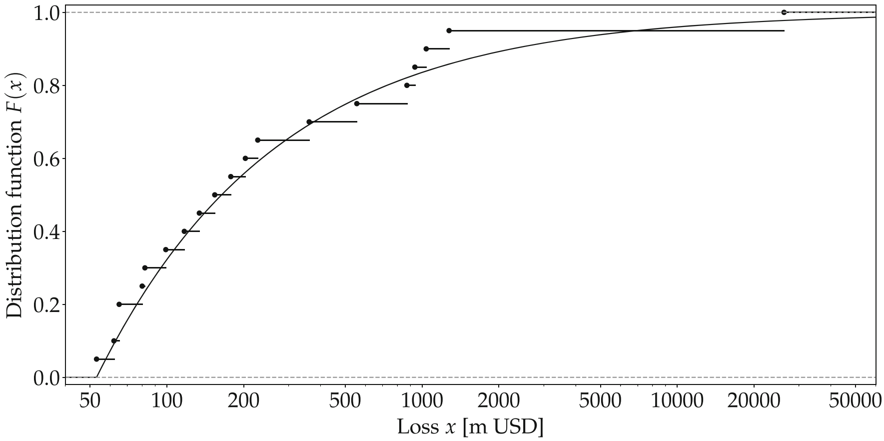

Fig. 1 Fitted Pareto distribution function

This procedure was implemented by iteratively deploying the Python function `scipy.stats.pareto.fit()` [12]. It converged on an optimal estimator $\tilde{\alpha}_f = 0.6405$.

Figure 1 plots the fitted Pareto distribution as specified by x_0 and $\tilde{\alpha}_f$. The empirical distribution function $F_n(x)$ is indicated by black dots, and the fitted distribution function is shown as a solid black curve. As the distribution function $F_X(x, \alpha)$ converges to 1 the faster the more α increases, predicted loss increases as α decreases.

The numerical magnitude of α therefore reflects the firms' loss expectation. To calculate risk premiums for natural disasters, firms in the commercial reinsurance industry use α's between 1.5 and 1.8 for fire, between 0.8 and 1.3 for windstorm, and between 0.6 and 1.0 for earthquake peril [20]. These values far exceed our estimate for $\tilde{\alpha}_f = 0.6405$. Figure 2 plots these differences, suggesting that the risk premium for insurance against intentional attacks will far exceed the premium paid for insurance against natural disasters.

This risk premium can be specified as

$$\mathfrak{R} = \mathrm{VaR}_\beta + C_f + C_v + B, \text{ for } \{C_f, C_v, B\} \in \mathbb{R}_{\geq 0} \tag{9}$$

where C_f represents the fixed costs, C_v the variable costs, B the profit and $\mathrm{VaR}_\beta(X)$ is the value at risk (VaR). This probabilistic term captures the risk of loss or impairment of any insured assets subject to an event threshold β. Its value approximately corresponds to the premium the infrastructure operator must pay to receive coverage. Exploiting the fact that this risk can be captured by a Pareto distribution function when extreme events are considered [23], VaR simply corresponds to the minimum value of x for which the distribution function $F_X(x, \alpha)$

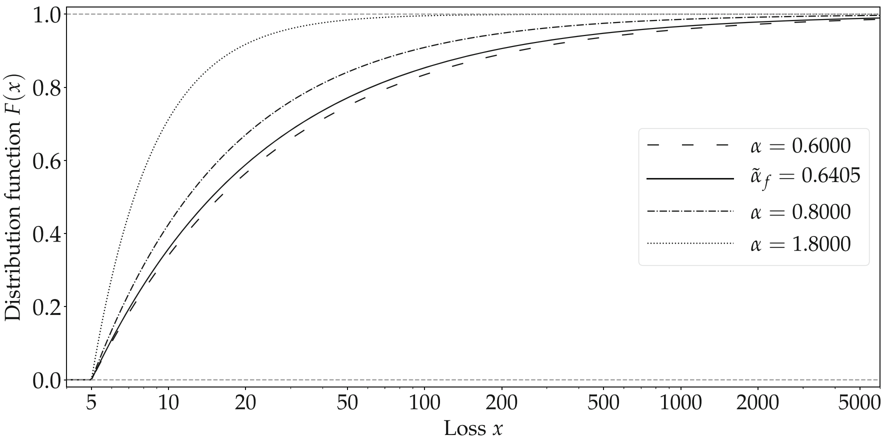

Fig. 2 Convergence of the Pareto distribution as a function of α

equals the event threshold β, formally:

$$\mathrm{VaR}_\beta(X) = F_X{}^{-1}(x, \alpha) = \min(x : F_X(x, \alpha) \geq \beta) \tag{10}$$

Then, integrating (1) in (10) yields

$$\mathrm{VaR}_\beta(X) = \frac{x_0}{\sqrt[\alpha]{1-\beta}} \tag{11}$$

Finally, VaR calculation requires a specification of return time, i.e. the period between any given occurrence of an extreme event and the next occurrence of such an event. Considering (1), this return time T can be specified as a function of beta [5]:

$$T = \frac{1}{1-\beta} \tag{12}$$

Using (11) and (12) with the data in Table 2, we can now calculate VaR as a function of β. Table 3 provides results for selected β values. Considering that the commercial insurance industry uses a standard level of $\beta = 0.95$, an insurance firm can expect a minimum loss of USD 5696 million once every 20 years.

Moreover, the values in Table 3 represent but a lower bound of expected loss, i.e. they give the minimum risk cover that any insurer would have to provide. As according to (9), the fixed and variable cost of operation have to be considered also, actual risk premiums are likely higher. Finally, Table 3 suggests that expected loss grows exponentially as β increases, implying that the firm faces a high risk of bankruptcy even if the extreme event occurs only rarely.

Table 3 VaR for different event thresholds β

β	$\text{VaR}_\beta(X)$ [m USD]	T [years]
50.0%	157	2
90.0%	1930	10
95.0%	5696	20
99.0%	70,270	100
99.6%	293,800	250
99.9%	2,558,672	1000

3 Simulation of Bankruptcy Risk

To simulate the economic situation of the insurance firm, particularly, its risk of going out of business as a result of an extreme event occurring, we use an adapted SIR model. Often used in epidemiology, the standard SIR model tracks a population as an infection spreads, grouping individuals into a susceptible (S), infected (I), and recovered (R) compartment. The dynamic spread is captured by an incidence rate γ and a recovery rate λ [13].

We suggest that can be adapted to our setting. The compartment S can be reinterpreted as the insurer's cumulative net profit. As our simulation begins at $t = 0$, S starts at zero, hence $S(t = 0) = 0$. Accumulation of this profit over time crucially depends on whether or not an extreme event occurs. If it does, the insurance firm incurs a loss since high damage-related payouts far exceed the risk premiums paid by operators. Otherwise, it makes a profit as it avoids such payouts but still earns risk premiums. The insurance firm has an incentive to accumulate profits in eventless periods in order to finance payouts in periods when an event occurs. Thus, the compartment R can be reinterpreted as the 'recovery contribution' to accumulated net profit, such that this profit increases whenever an extreme event does not occur ($R > 0$) and vice versa ($R \leq 0$). Hence, accumulated net profit can be written as:

$$S_{t+1} = S_t + R_t \tag{13}$$

Finally, the compartment I can be reinterpreted as an 'infected' asset (i.e. one that is covered by insurance and damaged or destroyed by an intentional attack). Hence, the recovery contribution R_t can be calculated as the difference between VaR and the loss the insurance suffers at time t, formally:

$$R_t = \text{VaR}_\beta - I_t \tag{14}$$

For the sake of simplicity, fixed and variable costs are omitted in this calculation. Since we use a Pareto distribution function to model the occurrence of extreme events, I_t has a Pareto distribution:

$$I_t \sim PA(x_0, \alpha) \tag{15}$$

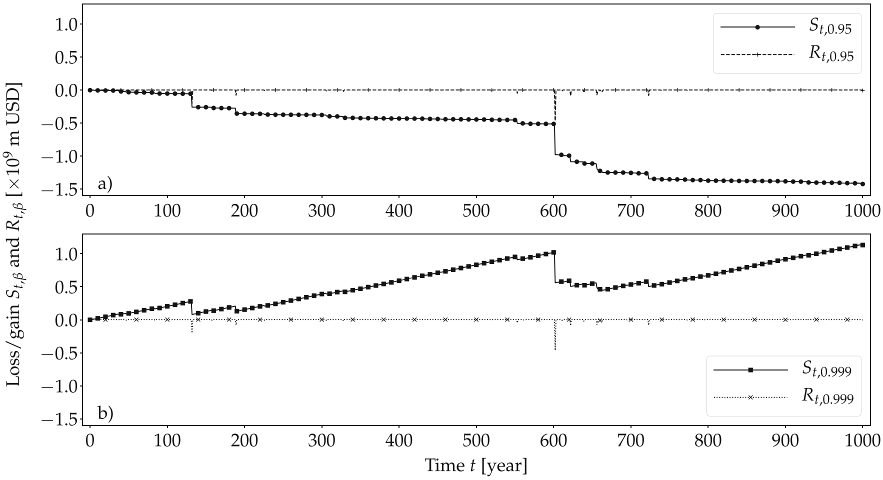

Fig. 3 Accumulated net profit for extreme event occurring late

Our setting considers discrete events that appear in an unpredictable sequence over time. Hence, rather than following the original SIR model which specifies fixed parameters for incident and recovery rates, we use a Pareto randomization process by deploying the Python function `scipy.stats.pareto.rvs()` [12] to produce numeric values for I_t based on the estimators for x_0 and $\tilde{\alpha}_f$ we found in the preceding section. Each randomization round is based on a time interval of $T = 1000$ years. The randomization process comprises 10,000 rounds.

Figure 3 shows a simulation where an extreme event occurs after $t = 602$ years of operations, i.e. relatively late. The upper panel uses $\beta = 0.95$ for VaR calculation, and the lower panel uses $\beta = 0.999$.

The firm has accumulated profits over the first 601 periods of its operations. However, for the case of $\beta = 0.95$ even these significant savings cannot offset the loss inflicted by the extreme event. Over the complete timespan, the accumulated loss amounts to 1.4244 billion USD. It is not until β is increased to 0.999 that an accumulated profit of 1.1311 billion USD results. Hence, even in the case that the extreme event occurs relatively late, insurance companies would have to charge very high risk premiums.

Figure 4 details the case that the extreme event occurs after only $t = 55$ years, i.e. very early. Both panels use the same VaR specifications as in Fig. 3. They suggest that the firm can never recover from the accumulated net loss even if operations are continued for the remaining 945 years, and it can never reestablish profitability. For $\beta = 0.95$ (0.999), accumulated loss is 18.35 (16.379) billion USD at $T = 1000$.

Since there is an infinite number of possibilities for both the time at which the extreme event occurs and the magnitude of the damage it inflicts, the firm can neither generate reliable pricing information for risk premiums, nor can it predict

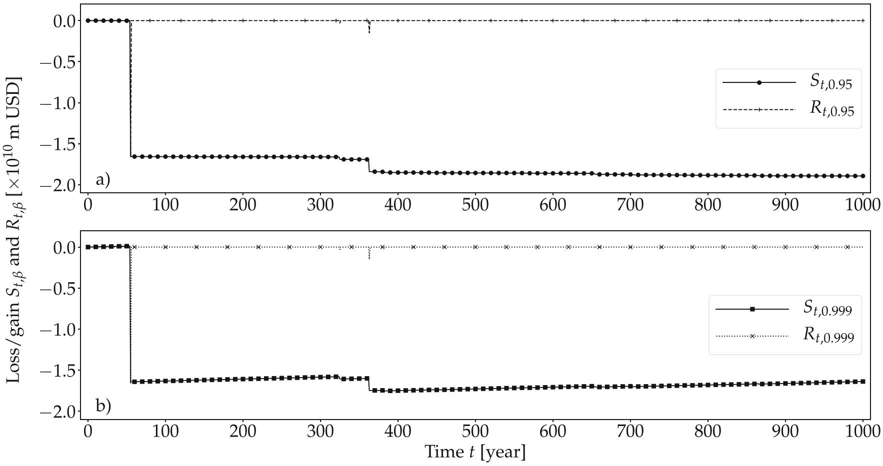

Fig. 4 Accumulated net profit for extreme event occurring early

the probability with which it may go out of business. Hence, the fate of an insurance company is essentially left to chance once it offers insurance for non-probabilistic extreme events.

4 Conclusion

Probabilistic events that occur at random, such as weather-related damage, can be captured and predicted by stochastic models [22]. As a result, insurance firms can offer coverage for such events since they can measure the variability of past events and compare expected losses to the mean or the median of past losses in order to calculate a risk premium.

By contrast, the analysis of non-probabilistic events such as intentional attacks require a deterministic approach that must make qualitative assumptions about possible worst-case scenarios. The results of such models hence crucially depend on the assumptions made and the corresponding risk scenarios. Our approach to risk modeling featured in this chapter illustrates this fundamental problem. The way we determine the scale and shape parameters of our Pareto distribution is deterministic. In particular, we assume that data on past observed events are representative of future damage. However, there is no other way to assess risks that have not yet been observed. The challenge is hence to develop an extensive catalogue of extreme events and to reliably estimate the business risk if they occur. As long as such predictions cannot be made, an insurance firm is highly unlikely to offer any coverage, and any reinsurer would most probably refuse to underwrite such risk. It should be noted that our estimates merely constitute lower boundaries of the actual damage, since the failure of key infrastructure, such as electricity or drinking water supply, may cause secondary damage in other sectors of the economy [1, 2, 8, 11, 25, 26, 30].

Since private firms are unlikely to offer insurance for intentional attacks, are there any alternatives operators could turn to? There have been proposals to use the capital market—and, in particular, private risk-taking investment—to provide coverage [18]. For example, insurance-linked securities (ILS) have been created to raise funding for coverage in the capital markets. Such 'catastrophe bonds' allow the issuer to share peak catastrophe risks with institutional investors who are disconnected from reinsurance markets [17]. It may hence be possible to issue 'infrastructure terror bonds', although, to the best of our knowledge, no such bonds have been issued in the industry. Further, since publicly issued bonds require a proper evaluation from a rating agency, the issuers would have to rely on third-party terrorism risk models.

Public-private initiatives have proposed 'terrorism pools' as a solution. The idea is to create a national fund, backed by state-level guarantees, that could collect enough financial means to provide coverage for intentional attacks.

Although these initiatives differ, they share a similar operational structure [19]. Private insurance companies provide a basic retention D. Over and above this amount, up to a pre-defined aggregate limit C, excess coverage is provided by the reinsurance market. If the aggregated loss L should exceed the sum of D and C, the government would cover the difference. While the idea seems appealing, only about one third of all OECD member countries offer such a national terrorism risk insurance program. Further, given the extreme losses inflicted by intentional damage of infrastructure, it remains questionable for how long the government can afford to compensate the loss not covered by private insurers and reinsurers. Operators should therefore expect that neither private industry nor the government are willing or able to provide insurance for intentional attacks on critical infrastructure.

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