

Approaching risks using the Extreme Value Theory

- An Application on MTPL -

Pomeriggio Attuariale del 4 Dicembre 2014 - Torino

Valerio Amante - Department of Statistical Science, La Sapienza.

valerio.amante@uniroma1.it

amante@studiosavelli.it

Comitato Regionale del Piemonte



Studio
Attuariale
Savelli

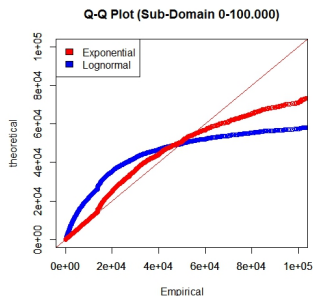
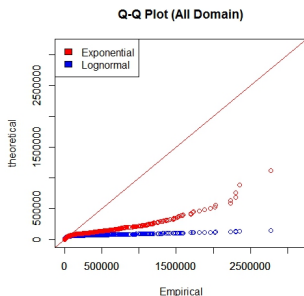
- Considering a real case study referred to a Non-Life insurance company operating in MTPL business, the aim of this work is to model the claim-size;
- In particular, using results of Extreme Value Theory, we will focus on the upper tail of that distribution;
- For this purpose, the way to define large claims becomes a sensible issue. This topic is relevant in the actuarial literature, as connected to the definition of Reinsurance Policy, Solvency Model, and Risk Manage.

The Framework - Fitting's problem

The aggregate claim amount \tilde{X} is well described by a compound process as the sum of a random number \tilde{K} of random variable \tilde{Z}_i (i.i.d), with \tilde{Z} and \tilde{K} independent:

$$\tilde{X} = \sum_{i=1}^{\tilde{K}} \tilde{Z}_i \quad \oplus \text{ Daykin, Pentikainen, Pesonen (1994)}$$

Generally, and also in our case, the calibration of the unique domain of claim-size doesn't give an acceptable fit using traditional distribution



Separate attritional and large claims

⊕ Swiss Solvency Test Approach

$$\tilde{X} = \tilde{X}_{Att} + \tilde{X}_{Lar} = \sum_{i=1}^{\tilde{K}_{Att}} \tilde{Z}_{Att,i} + \sum_{i=1}^{\tilde{K}_{Lar}} \tilde{Z}_{Lar,i}$$

- \tilde{X}_{Att} and \tilde{X}_{Lar} independent;
- \tilde{X} obtained by convolution of \tilde{X}_{Att} and \tilde{X}_{Lar}

Make a mixture of different distribution

⊕ Savelli, Clemente, Zappa (2014)

$$\tilde{X} = \sum_{i=1}^{\tilde{K}} \tilde{Z}_i$$

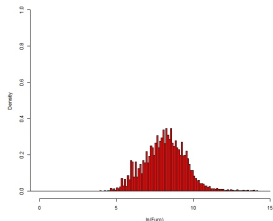
- \tilde{Z} obtained by mixture of distribution;

In this context, we use tools of Extreme Value Theory for the identification of Cut-off and calibration of claim-size distribution over this threshold.

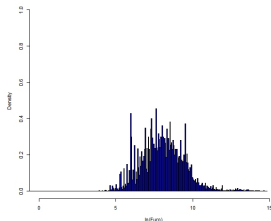
Insurance Claims Dataset - (MTPL LoB) - No Card

| | 2011 | 2012 | 2013 |
|--------------------|-----------|-----------|-----------|
| Mean | 14.451 | 14.814 | 12.356 |
| Standard Deviation | 83.288 | 87.713 | 68.252 |
| CoV | 5,8 | 5,9 | 5,5 |
| Skewness | 16,6 | 15,8 | 15,7 |
| Kurtosis | 365,6 | 325,6 | 317,6 |
| Percentile 50% | 3.544 | 2.963 | 3.000 |
| Percentile 75% | 8.443 | 7.590 | 8.800 |
| Percentile 95% | 31.207 | 30.360 | 27.400 |
| Percentile 99.5% | 500.643 | 526.423 | 440.585 |
| Max | 3.127.080 | 2.766.371 | 2.300.000 |
| Num. Oss. | 14.539 | 12.189 | 10.084 |

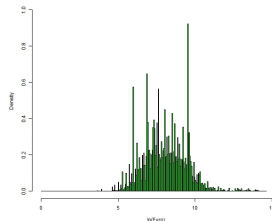
Empirical Distribution (ln) - 2011



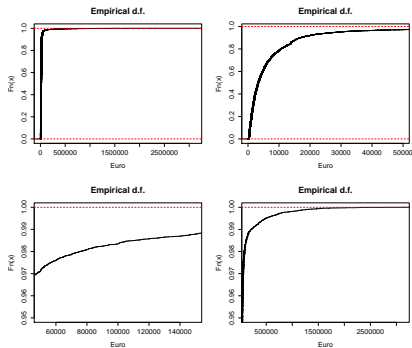
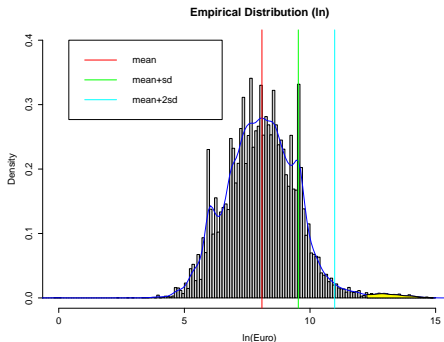
Empirical Distribution (ln) - 2012



Empirical Distribution (ln) - 2013



Insurance Claims Dataset - (MTPL LoB)

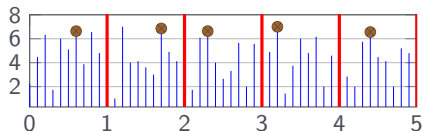


| Main Characteristics Empirical Distribution | | | | | | | |
|---|--------|------------------------|--------|------------------------|--------|------------------------|-----------|
| N.Obs | 36.812 | Skewness | 16,36 | Median | 3.150 | 99 th Perc. | 208.472 |
| Mean | 13.997 | Kurtosis | 353,40 | 75 th Perc. | 8.235 | Min | 0,5 |
| St. Dev. | 81.019 | 10 th Perc. | 500 | 95 th Perc. | 29.266 | Max | 3.127.080 |
| CoV | 5,79 | 25 st Perc. | 1.251 | | | | |

Extreme Value Theory: Parametric Approach

⊕ Embrechts, Klüppelberg, Mikosch (1997)

Block Maxima Method (GEV)



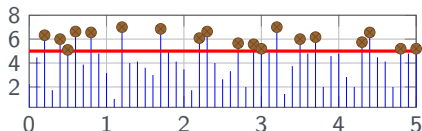
Fisher and Tippett (1928), Gnedenko (1943)

Let (X_n) be a sequence of i.i.d. r.v. If there are constants $c_n > 0$, $d_n \in \mathbb{R}$ and some non-degenerate df H such that $(M_n - d_n)c_n^{-1} \xrightarrow{d} H$ then H belongs to one of:

$$H_\xi(x) = \begin{cases} \exp\{-(1 + \xi x)^{-1/\xi}\} & \xi \neq 0 \\ \exp\{-\exp -x\} & \xi = 0 \end{cases}$$

| | |
|---------|-----------|
| Fréchet | $\xi > 0$ |
| Gumbel | $\xi = 0$ |
| Weibull | $\xi < 0$ |

Threshold Exceedances Method (GPD)



Pickands (1975), Balkema and de Hann (1974)

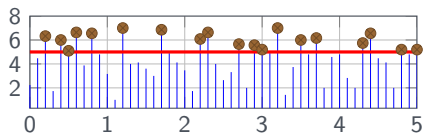
For a large class of underlying distribution functions F the conditional excess distribution function F_u , for u large, is well approximated by

$$F_u(y) = P(X \leq u + y \mid X > u) \approx G_{\xi, \beta(u)}(y) \quad u \rightarrow \infty$$

where $G_{\xi, \beta}(x)$ is the generalized Pareto distribution:

$$G_{\xi, \beta}(x) = \begin{cases} 1 - (1 + \frac{\xi x}{\beta})^{-1/\xi} & \xi \neq 0 \\ 1 - e^{(-x/\beta)} & \xi = 0 \end{cases}$$

Threshold Exceedances Method (GPD)



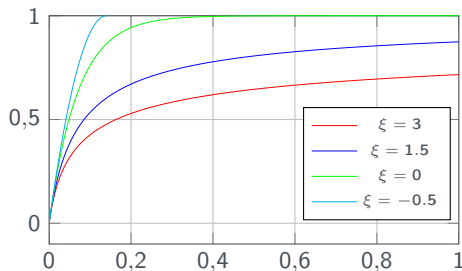
Generalized Pareto distribution (GPD)

$$G_{\xi, \beta}(x) = \begin{cases} 1 - (1 + \frac{\xi x}{\beta})^{-\frac{1}{\xi}} & \xi \neq 0 \\ 1 - e^{(-\frac{x}{\beta})} & \xi = 0 \end{cases}$$

where β scale parameter, ξ shape parameter:

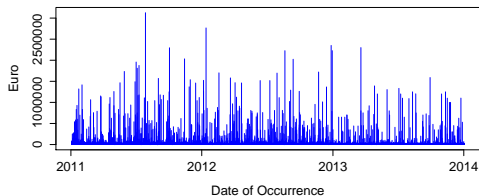
- $x \geq 0$ when $\xi \geq 0$;
- $0 \leq x \leq -\frac{\beta}{\xi}$ when $\xi < 0$;
- if $\xi > 0$ GPD is heavy-tailed and $E(X^k) < \infty$ for $k < \frac{1}{\xi}$

GPD for different shape value

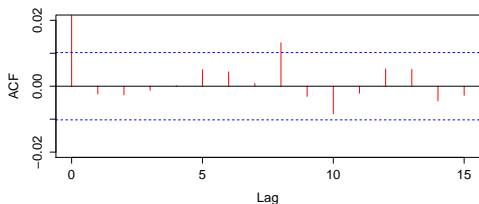


Verify the hypothesis of independence

No Card Claims Ammount



Autocorrelation Function



The basic assumption (more restrictive in financial times series) in EVT is that data be iid.

Casuality Test

Difference Sign

Turning Point

$$\frac{S - \frac{1}{2}(n-1)}{\sqrt{\frac{n+1}{12}}} \sim N(0, 1) \quad \frac{T - \frac{2}{3}(n-2)}{\sqrt{\frac{16n-29}{90}}} \sim N(0, 1)$$

H0=acc. (0.1537)

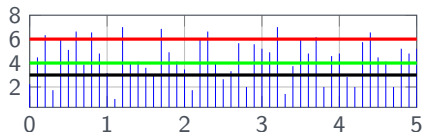
H0=acc. (1.618)

Def: Sample Autocorrelation function

$$\hat{\rho}(h) = \frac{\sum_{t=1}^{n-h} (x_t - \bar{x})(x_{t+h} - \bar{x})}{\sum_{t=1}^n (x_t - \bar{x})^2}$$

The challenge: Setting the Cut-off

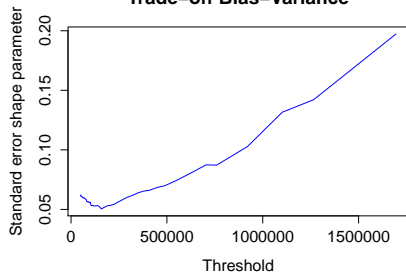
Which Level of threshold?



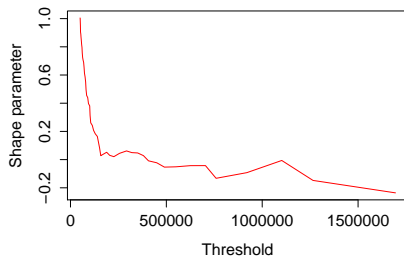
The determination of a cut-off is not easy, since it involves a trade-off between bias and variance:

- if the number of exceedance is set too high, many data are included in the tail of the distribution, even if not extreme, yielding biased parameter estimates;
- on the other hand, low values of numbers of exceedance give fewer observations of extreme data, resulting in inefficient estimates of the parameters, with huge standard errors.

Trade-off Bias-Variance



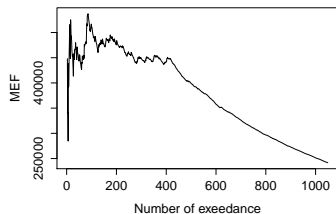
Plot Threshold-Shape



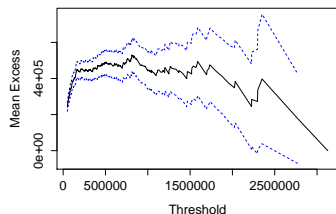
The challenge: Setting the Cut-off

⊕ McNeil, Frey, Embrechts (2005)

Mean Excess Plot



Mean Excess Plot



Excess over higher thresholds

Let F be a distribution with endpoint x_F and for some high threshold u we have $F_u(x) = G_{\xi, \beta}(x)$. From this we can infer model for higher threshold:

$$F_v(x) = G_{\xi, \beta + \xi(v-u)}(x) \quad e(v) = \frac{\xi v}{1 - \xi} + \frac{\beta - \xi u}{1 - \xi}$$

The function remains a GDP with the same shape but a scaling that grows linearly with the threshold v . The linearity of the mean is used as a diagnostic:

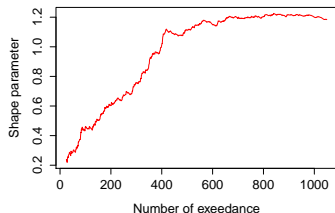
$$e_n(u) = \frac{\sum_{i=1}^n (X_i - u) I_{\{X_i > u\}}}{\sum_{i=1}^n I_{\{X_i > u\}}}$$

- Linear upward trend indicates a GDP with shape $\xi > 0$
- A plot tending toward horizontal indicates a GDP with shape $\xi = 0$
- A Linear downward trend indicates a GDP with shape $\xi < 0$

The challenge: Setting the Cut-off

⊕ McNeil, Frey, Embrechts (2005)

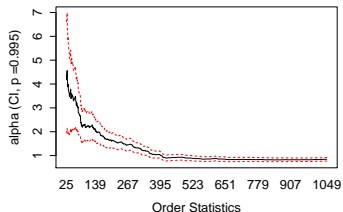
Hill plot



Number of exceedance

Threshold

1470000 355000 135000 79500 56700



Order Statistics

Hill estimator Plot

The inverse of the average log-exceedance above the threshold $\ln X_{k,n}$

$$\hat{\alpha}_{k,n} = \left[\frac{\sum_{j=1}^k (\ln X_{j,n} - \ln X_{k,n})}{k} \right]^{-1}$$

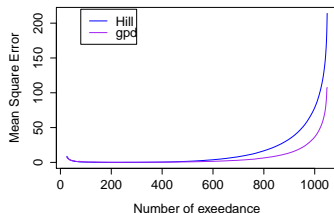
It's a well known different approach from parametric via to estimate tail index, that have good asymptotic properties

- Weak consistency - $\hat{\alpha}_{k,n} \xrightarrow{P} \alpha$ if $k \rightarrow \infty$ and $k/n \rightarrow 0$ for $n \rightarrow \infty$
- Strong consistency - $\hat{\alpha}_{k,n} \xrightarrow{a.s.} \alpha$ if $k/n \rightarrow 0$ and $k/\ln \ln n \rightarrow \infty$ for $n \rightarrow \infty$
- Asymptotic normality - $\sqrt{k}(\hat{\alpha}_{k,n} - \alpha) \xrightarrow{d} N(0, \alpha^2)$

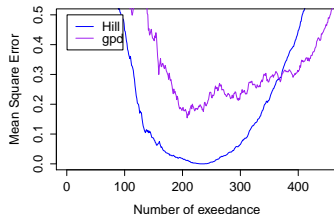
A challenge: Setting the Cut-off

⊕ Longin, Solnik (2001)

MSE



MSE



Monte Carlo Simulation and minimization of MSE

The procedure can be divided in three steps:

- 1 First we simulate S observations containing claims amount from a distribution $F \in MDA(H_\xi)$
The tail index ξ is related to ϕ by $\xi = f(\phi)$
- 2 For different numbers n of return exceedances, we obtain a tail index estimate $\hat{\xi}$;
- 3 Calculate the MSE (via the following formula) and choose k that minimize it:

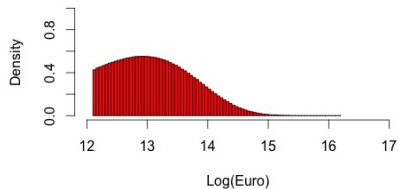
$$\begin{aligned}MSE(\hat{\xi}) &= E[(\hat{\xi} - \xi)]^2 + \text{Var}(\xi) \\ &= (\bar{\xi} - \xi)^2 + \frac{1}{S} \sum_{s=1}^S (\hat{\xi}_s - \xi)^2\end{aligned}$$

with $\bar{\xi}$ the mean of S simulated observation.

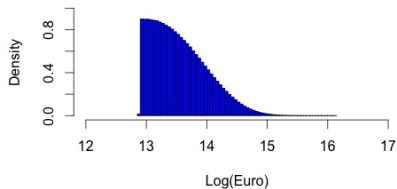
Fitting GDP to the Data

| | Threshold 180K | Threshold 400K |
|----------|----------------|----------------|
| Mean | 622.348 | 859.117 |
| SD | 465.042 | 472.392 |
| CoV | 0,75 | 0,55 |
| Skewness | 2,3 | 2,2 |
| Kurtosis | 11,9 | 10,5 |

GDP - Threshold 180K

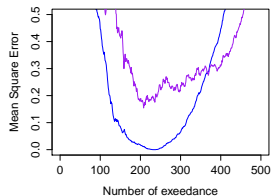


GDP - Threshold 400K

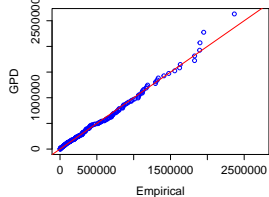


Fitting GDP to the Data

Mean Square Error Minimization



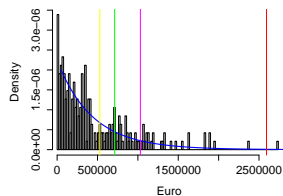
Q-Q Plot (GDP vs Empirical >400k)



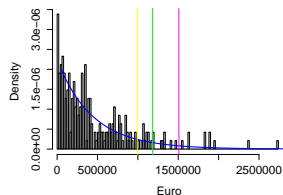
```
$threshold  
[1] 4e+05  
$n.exceed  
[1] 236  
$method  
[1] "ml"  
$par.est  
xi beta  
2.779602e-02 4.464518e+05  
$riskmeasures
```

```
p quantile sfall  
[1,] 0.250 528951.1 991854.1  
[2,] 0.500 712457.2 1180606.8  
[3,] 0.750 1030992.8 1508249.5  
[4,] 0.990 2593374.5 3115300.8  
$TVAR/VAR  
1.875134  
1.657092  
1.462910  
1.201254
```

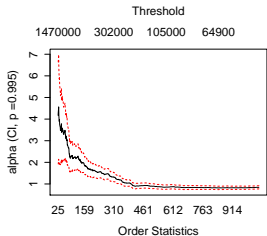
Var (GDP vs Empirical >400k)



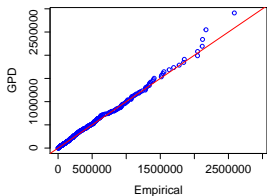
TVar (GDP vs Empirical >400k)



Fitting GDP to the Data



Q-Q Plot (GPD vs Empirical>180k)



```

$threshold
[1] 180000
$n.exceed
[1] 400
$method
[1] "ml"
$par.est$

```

```

xi      beta
4.768410e-02 4.211489e+05

```

```

$riskmeasures

```

```

p  quantile  sfall
[1,] 0.250  301991.8  750336.6
[2,] 0.500  476796.0  933893.6
[3,] 0.750  783565.6  1256023.7
[4,] 0.990  2348890.6  2899727.2

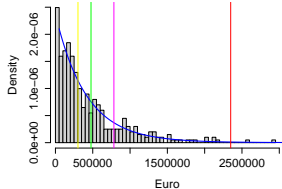
```

```

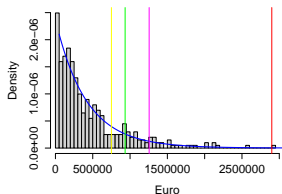
$TVAR/VAR
2.484626
1.958686
1.602959
1.234509

```

Var (GPD vs Empirical>180k)





TVar (GPD vs Empirical>180k)



- The choice of cut-off is a problem not easy to solve. In our case-study based on real data, every applied methodology identifies different thresholds.
- The results of every used methodology depend on distributional assumptions, mathematical properties associated with the model applied, reading of graphical tools. The attribution of greater credibility to a method rather than another is related to the awareness of the evaluator regarding the reasonableness of the tools used.
- Regarding future researches, my goal is to analyze the multivariate approach (with particular reference to Flooding, Hail and Hurricane losses)

Main references

-  Embrechts P., Klüppelberg C., Mikosh T. (1997), *Modelling Extremal Events*, Springer.
-  McNeil A., Frey R., Embrechts P. (2005), *Quantitative Risk Management*, Princeton.
-  de Haan L., Ferreira A. (2006), *Extreme Value Theory*, Springer.
-  McNeil A. (1999), *Estimating the Tails of Loss Severity Distributions using Extreme Value Theory*.
-  Klugman S., Panjer H., Willmot G. (2012), *Loss Models*, Wiley.
-  Wüthrich M., Merz M. (2013), *Financial Modeling, Actuarial Valuation and Solvency in Insurance*, Springer.
-  Savelli N., Clemente G.P., Zappa D. (2014), *Modelling and calibration for non-life underwriting risk: from empirical data to risk capital evaluation*, ICA2014.
-  Rocco M. (2011), *Extreme Value Theory for finance*, Questioni di Economia e Finanza.
-  Charpentier A. (2007), *Modeling and covering catastrophic risks*, AXA Risk College.
-  Longin F. and Solnik B.(2001), *Extreme Correlation of International Equity Markets*, The journal Of Finance.
-  Daykin C.D., Pentikainen T., Pesonen M. (1994), *Practical Risk Theory for Actuaries*, Chapman & Hall.