

# An Application of Extreme Value Theory for Measuring Financial Risk in the Uruguayan Pension Fund

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# Introduction

- Traditional statistical methods for financial risk measures fits models to all data even if primary focus is on extremes.
- In literatura → **normal** assumption for financial returns.
- This assumption provides a good approximation for the **average** of financial returns but does not provide a good fit for the **tail** of the distribution.
- The last 20 years → instabilities in financial markets → **volatility**.
- Search for more appropriate methodologies → **Extreme Value Theory**.

# Risk Measures

Suppose a random variable  $X$  with continuous distribution function  $F$  models losses on a certain financial portfolio over a certain time horizon.

- **Value at Risk:**

$$VaR_{\alpha} = F^{-1}(1 - \alpha)$$

- **Expected Shortfall:**

$$ES_{\alpha} = E(X | X > VaR_{\alpha})$$

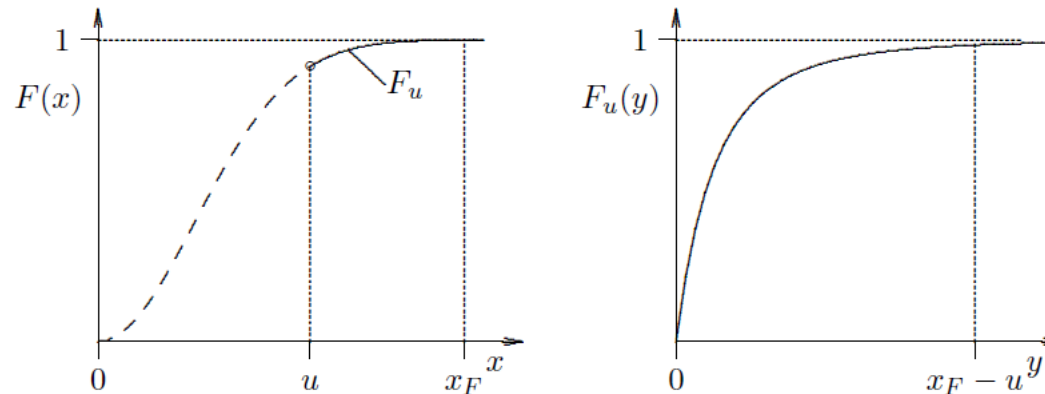
- **Return Level:**

$$R_k^m = H^{-1}(1 - 1/m)$$

If  $H$  is the distribution of the maximum observed over a successive non overlapping periods of equal length. For example, assuming a model for the annual maximum, the 15-years return level  $R_{365}^{15}$  is on average only exceeded in one year out of every 15 years.

# Extreme Value Theory

The Peak Over Threshold (POT) method, considers the distribution of exceedances over a certain threshold.



The distribution function  $F_u$  is called the excess distribution function and is:

$$F_u(y) = P(X - u \leq y | X > u) = \frac{F(u + y) - F(u)}{1 - F(u)}$$

# Extreme Value Theory

**Theorem Pickands (1975), Balkema and de Haan (1974).**

For a large class of underlying distribution  $F$ , the excess distribution function  $F_u$  can be approximated by GPD for increasing threshold  $u$ .

$$F_u(y) \approx G_{\xi, \beta}(y), \quad u \rightarrow \infty$$

where  $G_{\xi, \beta}$  is the Generalized Pareto Distribution (GPD) which is given by

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

for  $y \in [0, (x_F - u)]$  if  $\xi \geq 0$  and  $y \in [0, -\beta/\xi]$  if  $\xi < 0$ .

# Risk Measures under Extreme Value Theory

Assuming a GPD function for the tail distribution, if we denote  $x = u + y$  then

$$F(x) = (1 - F(u))F_u(y) + F(u)$$

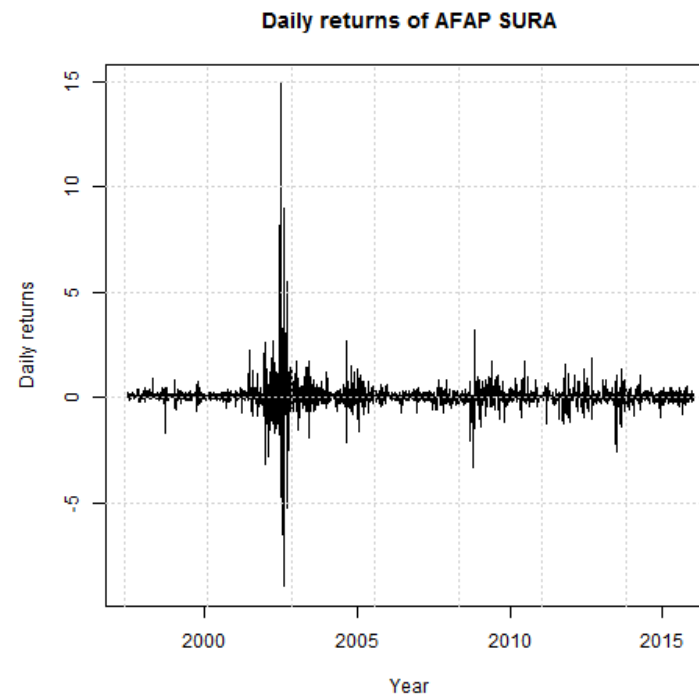
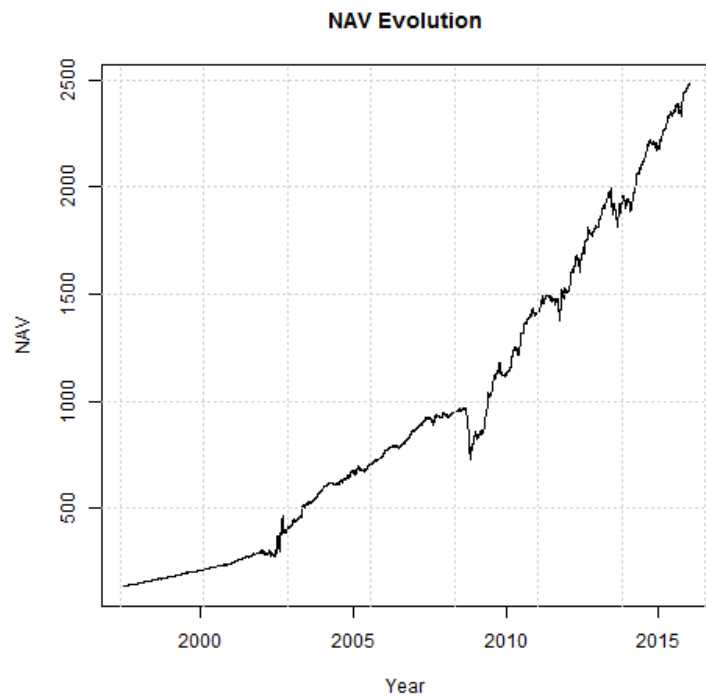
and replacing  $F_u$  by the GPD and  $F(u)$  by the empiric estimate  $(n - N_u)/n$ , where  $n$  is the total number of observations and  $N_u$  the number of observations above the threshold  $u$ .

$$VaR_\alpha = u + \frac{\beta}{\xi} \left( \left( \frac{n}{N_u} \alpha \right)^{-\xi} - 1 \right)$$

$$ES_\alpha = \frac{VaR_\alpha}{1 - \xi} + \frac{\beta - \xi u}{1 - \xi}$$

# Empirical Results

We work with the daily losses series of AFAP SURA NAV over a period of 18 years (1997-2015). Containing 4.802 trading days.

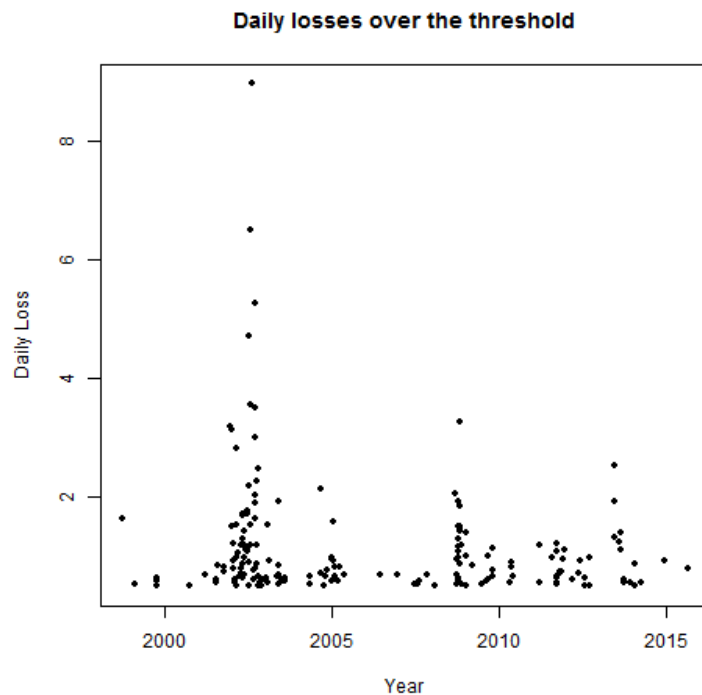


Don't appear to have a normal distribution

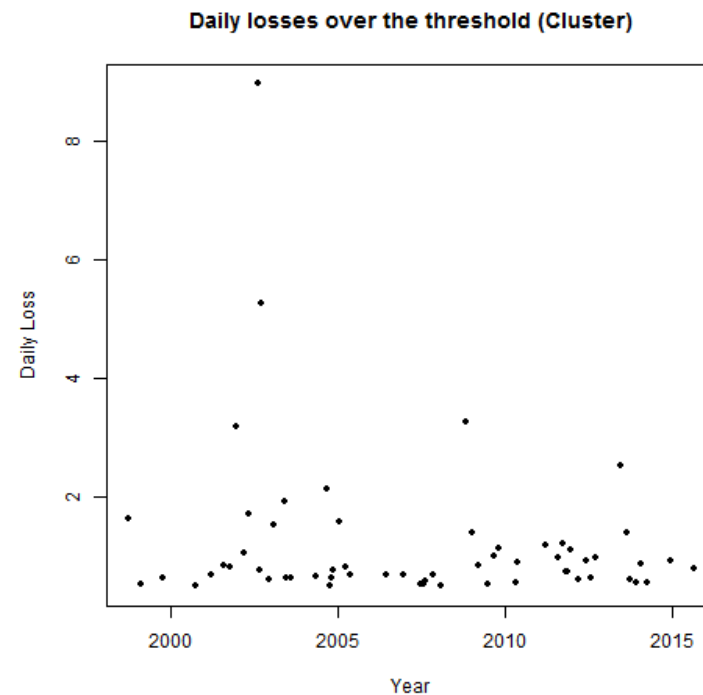
# Empirical Results

In practice, we have to consider two important aspects, the selection of the threshold  $u$  and the Independence of the exceedances.

$u = 0,5$



**182 exceedances**



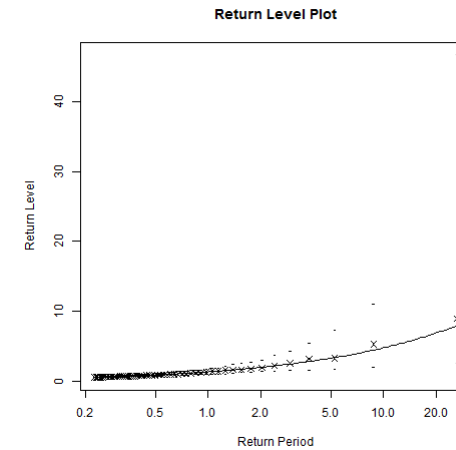
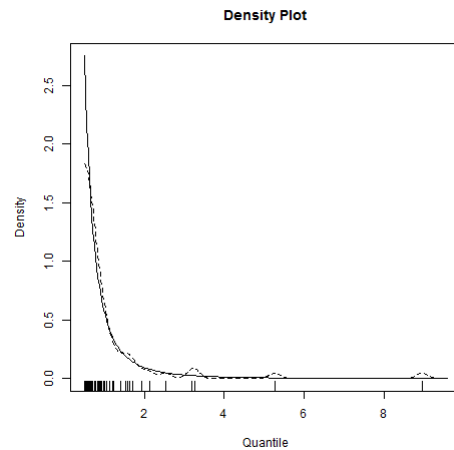
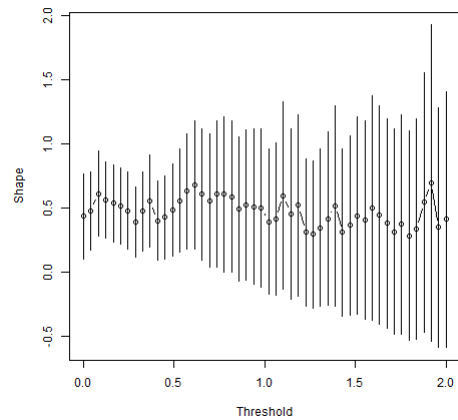
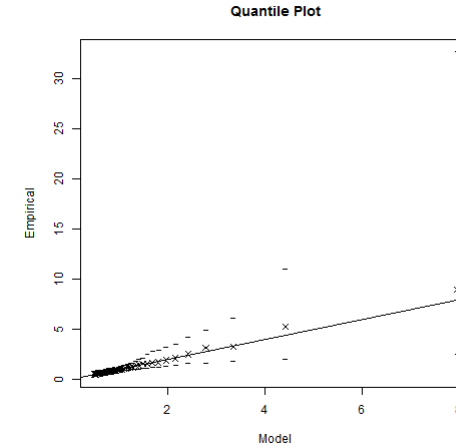
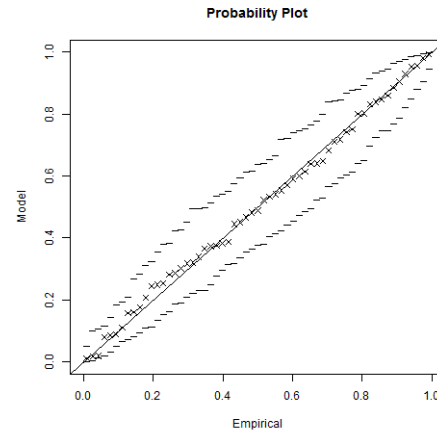
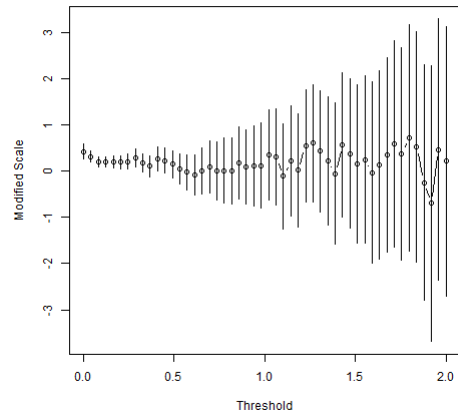
**59 exceedances**



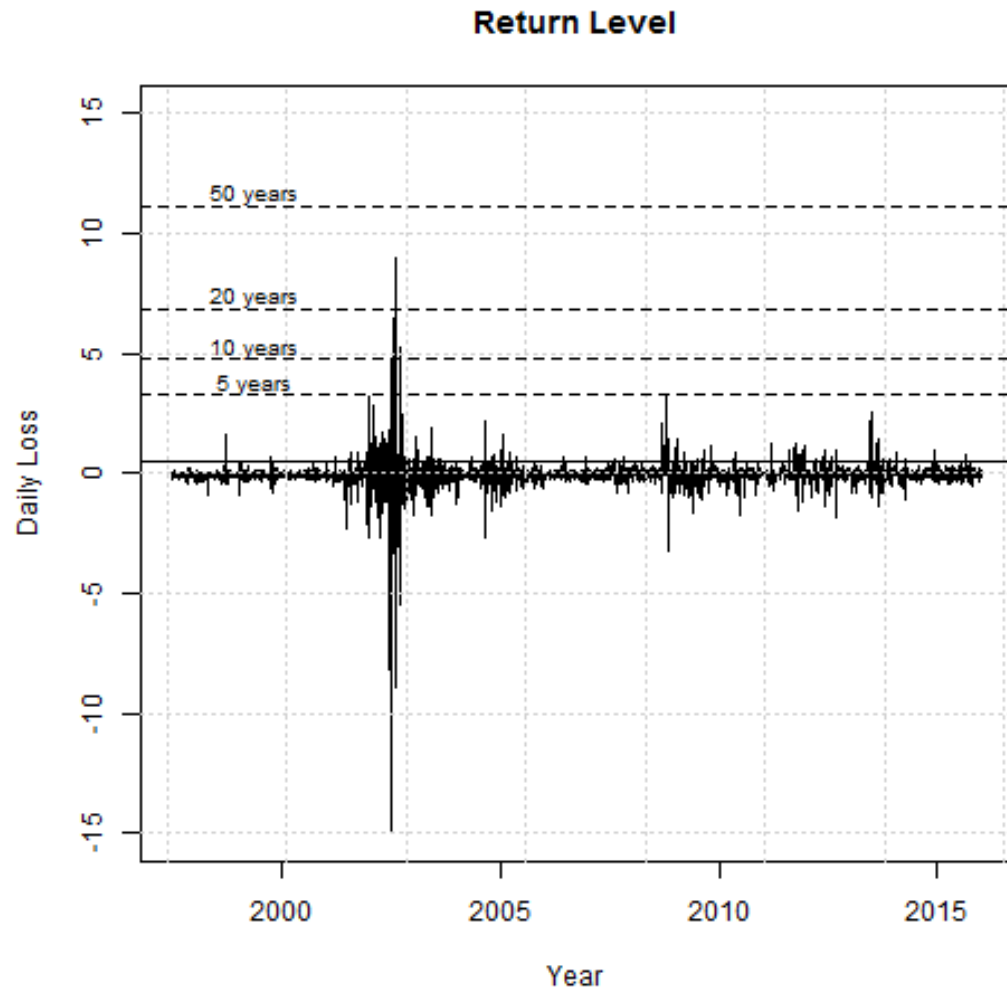
# Empirical Results

Selection of the threshold  $\rightarrow u = 0,5$

Diagnostic plots



# Empirical Results



## Return Level

5 years **3,26%**

10 years **4,75%**

20 years **6,88%**

50 years **11,14%**

# Empirical Results

The performance of the different methods can be evaluated by comparing the estimates with the actual losses observed.

	<b>high variance overestimates</b>		<b>heavy tail underestimates</b>	
Value at Risk: one day horizon				
	$\alpha = 5\%$	$\alpha = 2.5\%$	$\alpha = 1\%$	$\alpha = 0.5\%$
Normal model	0.808	0.975	1.169	1.301
GPD model	0.408	0.666	1.185	1.777
Empirical Result	0.397	0.664	1.201	1.769
Expected Shortfall: one day horizon				
	$\alpha = 5\%$	$\alpha = 2.5\%$	$\alpha = 1\%$	$\alpha = 0.5\%$
Normal model	1.030	1.175	1.348	1.468
GPD model	1.049	1.583	2.658	3.887
Empirical Result	0.991	1.468	2.314	3.134

**underestimates**  
**absence of extreme values**

# Conclusion

- Our major conclusion is that the POT model can be useful for assessing the **size** of extreme events.
- VaR approaches based on the normal assumption of normal distribution are definitely **overestimating** low percentiles, and **underestimating** high percentiles.
- The absence of extreme values in the assumption of normal distribution **underestimate** the ES estimation for high percentiles.
- The POT model seems **coherent** with respect to the actual losses observed and is **easy** to implement.

# References

## **Books**

- Coles (2001). An Introduction to Statistical Modelling of Extreme Values. Springer-Verlag, London.
- McNeil, Frey and Embrechts (2005). Quantitative Risk Management: Concepts, techniques and tools. Princeton University Press.

## **Articles**

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- Rockafeller, Uryasev (2002). Conditional value at risk for general loss distributions. Journal of Banking & Finance, Volume 26, Issue 7 1443-1471.

**Thank you!!!**