

ADVANCED OPERATIONAL RISK MODELING IN BANKS AND INSURANCE COMPANIES

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- References
- Definition and Classification
- Model Description
- Model Application

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Definition of Operational Risk

Operational risk definition given by Basel Committee on Banking Supervision in 2001 is: *"the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events"*.

Up to now this definition has been adopted for the insurance sector as well.

Classification of event types

- business disruption and system failures;
- clients, products and business practice;
- damage to physical assets;
- employment practice and workplace safety;
- execution delivery and process;
- external fraud;
- internal fraud.

The purpose of the research: Loss Distribution Approach

- Developing a comprehensive model to quantify the capital charge necessary to cover the Operational Risk in a financial institution.
- The proposed model belongs to the class of the “Loss Distribution Approach” (LDA). LDA is a frequency/severity model widely used in many fields of the actuarial practice.

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Model description:

Loss Distribution Approach

- Computation of the loss frequency and the loss severity distributions for each event type.
- Computation of the aggregate loss distribution for each event type as the convolution of the frequency and the severity of loss distributions.
- Determination of the aggregate annual loss Y_i , for event type i , as sum of the stochastic number N_i of events occurred in one year with severity Y_{ik} :

$$Y_i = \sum_{k=0}^{N_i} Y_{ik}$$

- Hypothesis: losses Y_{ik} are i.i.d. random variables; loss frequencies and loss severities are independent random variables.
- ➔ Monte Carlo simulation in order to generate a high number of simulated aggregated losses

Model description: Main issues

- The main issues in measuring the Operational Risk and the solutions that the model provides are:
 1. Database truncation (Solution: EM algorithm)
 2. Real dependencies among event types (Solution: Copula functions)
 3. Extreme events (Solution: EVT theory)
- Previous models consider only some of these points.

1. Database truncation (EM algorithm)

- The problem of determining the parameters of the distribution which represents empirical loss frequencies and loss severities is obviously influenced by the presence of “truncated data”.
 - it is necessary to apply the so called EM algorithm to evaluate the parameters of the unknown complete distribution.
- At this aim the conditional distributions and maximum likelihood estimation techniques involving truncated data are considered.
- Remark: in the numerical application, we will assume the standard hypothesis that the severity distribution follows a lognormal distribution.

1. Database truncation (EM algorithm)

- The two steps of the algorithm are:
 - 1) E-step: estimate the expected conditional value of the *loglikelihood* function $l_c = l_c(\theta)$ for the observed sample y and the current value for θ . Let denote θ_0 the initial value of the vector parameters (determined arbitrarily), we must then estimate:

$$Q(\theta; \theta_0) = E_{\theta_0} \{l_c(\theta) | y\}$$

- 2) M-step: the previous expression must be maximized with respect to θ :

$$Q(\theta_1; \theta_0) = \max Q(\theta; \theta_0)$$

→ These two steps are then repeated until convergence .

2. Real dependencies among event types (copula functions)

- The Student's copula is the copula of the multivariate Student's t -distribution:

$$C_{u,R}^n(u) = t_{u,R}^n(t_u^{-1}(u_1), L, t_u^{-1}(u_n))$$

- The t -Student copula is more flexible than the Archimedean one to simulate multivariate distributions with more than two marginals (Archimedean family possesses only one parameter).
- t has a tail dependence property.

3. Extreme events (EVT theory)

- EVT aims to describe the distributions of rare events focusing on the tail of the distribution.
- EVT is then a powerful tool for managing losses due to rare events and inadequacy of internal controls (Low Frequency High Impact Events).
- Extreme events can be treated considering the value that the random variable assumes over a given threshold (“*Peaks Over Threshold method*”, *POT*).

3. Extreme events (EVT theory)

- Given a random variable X with distribution function F , the excess distribution function (called excess conditional distribution function) above the fixed threshold k is

$$F_k(z) = \Pr\{x - k \leq z | x > k\}$$

- Pickand (1975) and Balkema - De Haan (1974) theorems: excess distribution can be approximated (for a certain class of distributions) for a high threshold k , by a generalized Pareto distribution:

$$G_{\xi, \sigma}(z) = \begin{cases} 1 - \left(1 + \frac{\xi}{\sigma} \cdot z\right)^{-\frac{1}{\xi}} & \xi \neq 0 \\ 1 - e^{-\frac{z}{\sigma}} & \xi = 0 \end{cases}$$

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Model application: database description

- The input data are taken from OpData, an operational losses database supplied by OpVantage, a division of Fitch Risk Management.
- The data collected from public sources (1972-2006), are losses whose amounts exceed a truncation threshold.
- We consider the database on the period 1994-2006, because previous data are not statistically significant.
- In the OpData, operational losses are categorized according to the Basel Committee's event types classification.
- Valuations can be "tailored" on the base of some characteristics like: geographical location, dimension of the bank, total assets/liabilities, ... and so on.

Model application: steps

- estimation of the parameters of frequency and severity distributions, for each event type applying the EM algorithm. The frequency of loss arising from each event type is assumed to be a Poisson distribution while the lognormal distribution is used to model the loss severity
- estimation of the aggregate loss distribution, for each event type, via Monte Carlo simulation;
- quantification of Operational Risk capital charge, for each event type, through risk measures such as Value at Risk and Expected Shortfall;
- quantification of the total Operational Risk capital charge in different hypothesis:
 - **perfect dependence** (comonotonicity) among event types. The total capital charge is obtained by summing capital charges for each event type → overestimation of the total Operational Risk capital charge
 - **independence** among event types → underestimation of the total Operational Risk capital charge;
 - **realistic dependence structure through a t-Student copula.**

Model application: steps

- We repeat the above steps using Extreme Value Theory to efficiently model the right tail of the severity distribution.
- We model the severity distribution using the lognormal distribution (in the left tail and in the centre) and the Generalized Pareto Distribution (GPD) for the right tail.

Model application: marginal distributions

- We apply then the EM algorithm to estimate the parameters of frequency and severity distributions:
- We consider a unitary capital (Total Assets = 1€)

Table 1. Parameters Estimation of severity and frequency distributions for each Event Type.

Event Type	Severity (lognormal)	Frequency (Poisson)
1.Clients, Products and Business Practices	$\bar{\mu} = -10.425 ; \bar{\sigma} = 2.286$	$\lambda = 37.130$
2.Employment Practices and Workplace Safety	$\bar{\mu} = -12.139 ; \bar{\sigma} = 2.066$	$\lambda = 6.686$
3.Execution, Delivery and Process Management	$\bar{\mu} = -11.456 ; \bar{\sigma} = 2.039$	$\lambda = 6.678$
4.External Fraud	$\bar{\mu} = -10.824 ; \bar{\sigma} = 1.975$	$\lambda = 13.741$
5.Internal Fraud	$\bar{\mu} = -10.692 ; \bar{\sigma} = 2.143$	$\lambda = 18.971$

Model application: risk measures for each event type

- Aggregate loss distribution, for each event type at firm level (Monte Carlo simulation with 100,000 replications):

Table 2. Value at Risk for Event Type.

Event Type	VaR 95%	VaR 99%	VaR 99.9%
1.Clients, Products and Business Practices	0.000564	0.001309	0.004634
2.Employment Practices and Workplace Safety	0.000045	0.000116	0.000411
3.Execution, Delivery and Process Management	0.000051	0.000133	0.000477
4.External Fraud	0.000092	0.000210	0.000637
5.Internal Fraud	0.000178	0.000431	0.001260
TOTAL	0.000929	0.002199	0.007419

Table 3. Expected Shortfall for Event Type.

Event Type	ES 95%	ES 99%	ES 99.9%
1.Clients, Products and Business Practices	0.001209	0.002871	0.009721
2.Employment Practices and Workplace Safety	0.000103	0.000243	0.000735
3.Execution, Delivery and Process Management	0.000121	0.000301	0.001043
4.External Fraud	0.000183	0.000398	0.001127
5.Internal Fraud	0.000366	0.000807	0.002224
TOTAL	0.001982	0.004620	0.014850

Model application: Capital charge with real dependence structure + EVT

- MC simulation copula + EVT:

Table 4. Operational Risk Capital Charge with EVT (% of total asset A).

OR Capital Charge	VaR 95%	VaR 99%	VaR 99.9%	ES 95%	ES 99%	ES 99.9%
Comonotonicity	0.000940	0.002368	0.009648	0.002263	0.005923	0.024049
t-Student Copula	0.000849	0.002132	0.008214	0.001972	0.004917	0.017879
Independence	0.000782	0.001749	0.006577	0.001684	0.004133	0.016445

Conclusions

- LDA Modeling for Operational Risk is a flexible tool for modeling operational risk; this kind of models come from the actuarial experience of the non life sector (that traditionally faces non gaussian distributions to model uncertainty and nonlinear correlated events); also Monte Carlo simulation was introduced since 1970 in actuarial science.
- Operational Loss Databases can provide all the necessary input data to feed the model and to calibrate the technical bases (assumptions) coherently with the characteristics of the single bank (dimension, geographical location, assets/liabilities, ...).
- From the calculation point of view all problems can be managed and solved: database truncation, correlations, tail dependences, tailored valuations.

Recapiti



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