Evaluation of Operational Risk by the Application of the LDA Method - The Case of Popular Bank

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Abstract: ***This paper examines operational risk and the advanced measurement approach to quantify it in order to determine the capital requirements to cover the resulting losses. The objective of this study is to evaluate the degree of exposure of Popular bank to operational risks through the advanced measurement approach and more specifically through the LDA (Loss Distribution Approach) model which is based on the aggregation of two data distributions estimated during the study: the severity distribution (which reflects the impact of the risk on the bank) and the frequency distribution (which reflects the probability of risk occurrence).***

Keywords: Operational Risk, Advanced Measurement Approach, LDA, Operational Risk Mapping

1. Introduction

Technological development and the evolution of the means of communication as well as the logistic means, have contributed to the increase in uncertainty and to the diversification of random factors that may affect the business continuity of economic operators and their solvency. The latter is dependent on market conditions, the creditworthiness of counterparties and the control of events caused by malfunctions in its various forms: human, process, system and external events.

Influenced by its environment, the financial system and in particular the banks are called to watch out for economic, political and social changes, by adopting appropriate risk management rules, including credit risk, market risk, operational risk, liquidity risk and rate risk.

These risks have been the subject of several global agreements, to quote: Basel 1, Basel 2 and Basel 3, with the objective of reducing their impact on the proper functioning of the financial system by implementing risk management standards based on identification, monitoring, measurement and coverage (allocation of own funds, outsourcing, insurance).

Admittedly, the repetitive financial crises and the losses experienced by some banks have revitalized the process of implementing standardized regulations to control the impact of unpredictable events related to each type of risk, but the eligibility constraints and the timetable foreseen by the regulator represent a challenge for the Moroccan banks.

Conscious of the contribution of such a vision, BANK AL MAGHRIB has opted since 2006 for the modernization of the banking sector and compliance with international standards and sound practices and in particular, the Basel agreements. Thereby, the banks have integrated this change process by complying with the rules dictated by BANK AL MAGHRIB on risk management and internal control.[1]

For the first time, the Basel 2 agreement, based on three pillars, integrated operational risk in the calculation of capital requirements by setting out capital calculation approaches and eligibility conditions.

At the level of operational risks, the calculation approaches, with the exception of the "basic indicator" method, are based on the knowledge of the credit institution, the identification and monitoring of risks through the establishment of risk mapping in order to control probable losses through better allocation of own funds.

The adoption of the AMA approach[2] is a strategic objective for the credit institution, as it is based on internal capital calculation models, which means optimisation of the capital allocation. This approach is accompanied by a risk management system, namely risk mapping and a system for identifying and collecting incidents necessary for statistical modelling.

Several methods are envisaged within the framework of the AMA approach of which the LDA method "LOSS DISTRIBUTION APPROCHE" remains the most widespread among specialists in the field. This method, based on the modelling of severity and frequency of occurrence, is very dependent on the quality of the database and the completeness of the recording of operational risk incidents.

In the risk management literature, the standard model used assumes that severity is modelled by the normal log distribution and frequency is modelled by Poisson distribution, this hypothesis ignores the adjustment of these laws with the empirical distributions of losses and frequencies.

Therefore, the objective of this work is to implement the advanced measurement approach in the case of the Popular bank. This approach is considered to be the most sophisticated operational risk measurement approach and

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[1] In applications of BANK AL MAGHRIB circulars N° 20/G/2006, N° 25/G/2006, N° 26/G/2006, N°27/G/2007, N° 40/G/2007, N° 5/G/2010, N° 7/G/2010 et N° 8/G/2010.

[2] Under the « advanced measures » approach, the regulatory capital requirement is the result of an internal measurement model owned by the bank and validated by the supervisory authority.

will be applied through the LDA (Loss Distribution Approach) model.

2. Literature Review

The use of the LDA model has been handled by several researchers and authors. They analyzed the process and the steps needed to implement it. In this sense, the collection of operational data, which is the preliminary step to the application of this measurement method, was handled by Chernobai and Al. (2006) who indicated that the data above the truncation threshold are those that fit into the adjustment of severity and frequency distributions.

In addition, Baud et al. (2002), Frachot et al. (2003), Fontnouvelle et al. (2003) and Chernobai et al. (2005a, 2005c) have also defended the importance of considering the truncation threshold in work that models operational losses. However, some authors such as Moudoulaud and Roncalli (2003) do not support this view, and state that this approach is not recommended if there are losses that are below the threshold and are of high frequency (their impact would be significant in this case).

On the other hand, estimating the severity distribution and frequency distribution is also a difficult task. In this context, Chernobai et al. (2005c) claim that the wrong choice of these distributions is likely to lead to undervaluation or overvaluation of regulatory capital.

To avoid such problems, several adjustment methods have been proposed. Indeed, Frachot et al. (2003), Chernobai et al. (2005a) and Bee (2006) opted for the lognormal method, being the easiest method to implement severity distribution adjustment, while other authors have chosen more complex methods using several variables such as GB2 and the g and h distribution using four parameters (Dutta and Perry, 2006). On frequency distribution, the majority of authors (Frachot et al. 2003, Chapelle et al. 2004, Dutta and Perry, 2006, Chernobai et al. 2005a, de Fontnouvelle et al. 2003) opt for the use of Poisson's Law as a modelling method.

Finally, aggregation of estimated distributions can be done by several methods. Analytical methods such as the inversion method or recursive method proposed by Klugman et al. 1998, Embrechts et al. (2003) in this context. These methods have the advantage of being easy and quick, but require the verification of certain assumptions concerning the independence between the severity and frequency of occurrence of operational incidents. On the other hand, Cruz, 2002, Frachot, Frachot and Roncalli (2001) propose a different method: the Monte Carlo simulation which does not take into account the assumptions made by the other methods and which offers high precision in the calculations.

3. Methodology of the Implementation of the LDA Approach

The calculation of risk capital for the LDA (Loss distribution approach) can be carried out either for each type of risk in each business line, for each risk category, or for the entire incident base. However, the use of each approach is conditioned by the richness of the database which will allow the base to be broken down into sub-samples respecting the minimum size necessary to carry out the statistical tests.

In our study, we will choose to model the entire sample regardless of the risk category or process involved. This approach is more appropriate, since it allows for a sufficient sample given on the one hand, the recent introduction of incident collection at the bank level and on the other, it makes it possible to avoid studying the correlation between the different events and the different business lines. As a result, only two distributions need to be modelled: the frequency of occurrence and the severity of losses.

The application of the LDA model will go through the following steps:
2.1. Estimation of severity distribution parameters and frequency;
2.2. The distributions fit tests;
2.3. Presentation of the LDA algorithm.

We will use statistical inference techniques including estimation techniques, distribution fit tests, and random variable simulation techniques.

3.1 Estimation of severity distribution parameters and frequency

For loss modelling, we will use the standard model log-normal law for severity distribution and the Poisson law for frequency of occurrence.

However, the fit test of these laws with empirical distributions will be performed to ensure the quality of fit and robustness of the model.

In this point, we will describe the characteristics of the log-normal law and the Poisson law respectively, as well as the parameter estimates from the empirical sample.

a) Estimation of log-normal law parameters:

Definition:
The density of the log-normal law is written:

$$f(x) = \begin{cases} \dfrac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{(\log x-\mu)^2}{2\sigma^2}} & \text{si } x \geq 0 \\ 0 \text{ sinon} \end{cases}$$

Estimation of parameters by maximum likelihood:
The likelihood function corresponds to the following product :

$$L(\mu, v) = \prod_{i=1}^{n} \frac{1}{X_i\sqrt{2\pi v}} e^{-\frac{(\log X_i-\mu)^2}{2v}}$$

Hence logarithm of L(μ,σ) is written:

$$M(\mu, v) = \log \prod_{i=1}^{n} \frac{1}{X_i \sqrt{2\pi v}} e^{-\frac{(\log X_i - \mu)^2}{2v}}$$

$$= \sum_{i=1}^{n} \log \frac{1}{X_i \sqrt{2\pi v}} e^{-\frac{(\log X_i - \mu)^2}{2v}}$$

$$= -\sum_{i=1}^{n} \log X_i - \frac{n}{2} \log 2\pi v - \frac{1}{2v} \sum_{i=1}^{n} (\log X_i - \mu)^2$$

The partial differentials for determining the domain values that maximize M(μ, v) are:

$$\frac{\partial M}{\partial \mu} = \frac{\partial}{\partial \mu}\left[-\sum_{i=1}^{N} logX_i - \frac{n}{2}\log 2\prod\sigma - \frac{1}{2v}\sum_{i=1}^{n}(logX_i - \mu)^2\right]$$

$$= -\frac{1}{2v}\sum_{i=1}^{n}\frac{\partial}{\partial \mu}(logX_i - \mu)^2$$

$$= -\frac{-2}{2v}\sum_{i=1}^{n}(logX_i - \mu) \quad = \frac{1}{v}\sum_{i=1}^{n} logX_i - n\mu)$$

$\frac{\partial M}{\partial \mu}$=0 implique que $\frac{1}{v}\sum_{i=1}^{n} logX_i - n\mu)$=0

-->$\sum_{i=1}^{n} logX_i = n\mu$ -->$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} logX_i$

We end up with a value of the parameter μ suitable to maximize M(μ, v) when it is used in conjunction with the value of v which we determine at the moment :

$$\frac{\partial M}{\partial v} = \frac{\partial}{\partial v}\left[-\sum_{i=1}^{n} X_i - \frac{n}{2}\log 2\pi v - \frac{1}{2v}\sum_{i=1}^{n}(\log X_i - \mu)^2\right]$$

$$= -\frac{n}{2}\frac{\partial}{\partial v}[\log 2\pi v] - \left(\frac{1}{2}\sum_{i=1}^{n}(\log X_i - \mu)^2\right)\frac{\partial}{\partial v}\left[\frac{1}{v}\right]$$

$$= -\frac{n}{2}\frac{2\pi}{2\pi v} - \frac{1}{2}\left(\sum_{i=1}^{n}(\log X_i - \mu)^2\right)\left(\frac{-1}{v^2}\right)$$

$$= -\frac{n}{2v} + \frac{1}{2v^2}\sum_{i=1}^{n}(\log X_i - \mu)^2$$

$$\frac{\partial M}{\partial v} = 0$$

$$\Rightarrow \quad -\frac{n}{2\hat{v}} + \frac{1}{2\hat{v}^2}\sum_{i=1}^{n}(\log X_i - \mu)^2 = 0$$

$$\Rightarrow \quad \frac{n}{2\hat{v}} = \frac{1}{2\hat{v}^2}\sum_{i=1}^{n}(\log X_i - \mu)^2$$

$$\Rightarrow \quad \hat{v} = \frac{1}{n}\sum_{i=1}^{n}(\log X_i - \mu)^2$$

Using the second derivative method, it is easy to show that the torque formed from these two estimators maximizes the function M(μ, v) and, by extension, L(μ, v).

b) Poisson distribution parameter estimation

Definition

The Poisson law is defined by the following formula :

P(x=k)=$\frac{\mu^k}{k!}e^{-\mu}$

Properties

E(X)= μ et VAR(X)= μ

The Poisson law is equiditributed

Estimation of the parameter μ by the maximum likelihood

The likelihood is given by:

L(μ)=$\prod_{i=1}^{n} P(x_{i,\mu})$=$\frac{\mu^{\sum_{i=1}^{n} x_i}}{\prod_{i=1}^{n} x_i!}e^{n\mu}$

Maximizing a function or maximizing its logarithm is equivalent so:

$$\ln[L(\mu)] = \ln(\mu)\sum_{i=1}^{n} x_i - \sum_{i=1}^{n}\ln(x_i!) - \mu n$$

We are now seeking to maximize it :

$$\frac{\partial \ln[L(\mu)]}{\partial \mu} = \frac{1}{\mu}\sum_{i=1}^{n} x_i - n = 0$$

And let us therefore obtain its only estimator of maximum likelihood which will be :

$$\hat{\mu} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

We then have the standard deviation estimate by the maximum likelihood:

$$\hat{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i}$$

3.2 The distributions fit tests

Kolmogorov-Smirnov (KS) fit test

In this study, we implemented fit tests to test the acceptability of the model. A hypothesis test will test the acceptability of the distribution. In fact, the null hypothesis and the alternative hypothesis can be formulated in this way :

H_0 : $F_X(x)$= F(x,θ);

H_1: $F_X(x) \neq$ F(x,θ);

With :

$F_X(x)$: The empirical distribution function

F(x;θ) : One of The empirical distribution functions studied.

Thereby, the model offers a good fit if the null hypothesis is not rejected.

We are building a Kolmogorov-Smirnov (KS) test to ensure that distributions are adjusted. The KS test measures the absolute maximum deviation between the empirical distribution function and that of the model. The KS statistic is calculated as follows:

$$KS = \sqrt{n} sup_x |(F_X(x) - F(x;\hat{\theta}))|$$

where $\hat{\theta}$ designates the vector of the estimated parameters.

This statistic is compared to a tabulated critical value. If the calculated statistic is less than the tabulated statistic, then the null hypothesis will not be rejected.

Good fit test « Chi square »

Chi square test χ^2 consists in calculating the Q statistic defined below, the distribution of which is χ^2_{n-r-1} and r the number of parameters to be estimated

$$\sum_{j}^{k}\frac{(n_j - E_j)^2}{E_j}$$

With:
n_j : Number of observations in group j, with j=1, …k ;
E_j : The expected number of observations in each group given that the model is correct and the parameters have their estimated values. It is calculated as follows :
E_j = n Pr(X∈ j th group) for j=1… k where n is the sample size and E_j >5

This statistic is compared to a tabulated critical value. Indeed, if Q exceeds χ^2_{n-r-1}, α (where d=k-r-1 is the number of degrees of freedom and α is the significance threshold) then the null hypothesis is rejected.

3.3 Presentation of the LDA algorithm

The calculation of venture capital (capital charge) consists in determining the value at risk defined as the value of the loss we are sure that we do not lose more with 99.9% chance in a period of a year.[3]

As a result, the Value at Risk is the inverse of the distribution function at point (0.999) which is:
VaR = $F^{-1}(0{,}999)$ with F is the distribution function for aggregate losses.

The determination of the VaR in our study is made by simulation of the variables in the framework of the Monte Carlo method. Thereby, the following algorithm is used to aggregate the loss data for the purpose of determining the distribution of annual losses and calculating the 99.9th percentile.

Thereby, we run this algorithm:
1) Generate n number of losses per year based on frequency distribution of loss data (Poisson) ;
2) Generate n loss amounts Xi (i=1… n) according to the estimated severity distribution of internal data per year ;
3) Sum all Xi amounts generated to have S ;
4) Repeat steps 1 to 3 30,000 times to obtain the distribution of annual losses ;
5) The CaR is calculated by taking the 99.9th percentile of the empirical distribution of annual losses.

4. Application of the Model and Results of the Case Study: Popular Bank

In this work, we chose the Bancassurance branch of the Popular bank, which represents an indispensable ancillary activity, in particular life insurance products that accompanies the private and professional credit chain and the property insurance products that accompany the investment credits. This situation makes the management of the dispatched bancassurance in the various entities of the bank (agency, guarantee service, branch, business centers), which forced us to consult the various stakeholders in this process.

[3] Paragraph 667, Basel Committee on Banking Supervision, International Convergence of Measurement and Capital Standards, June 2004a

As regards operational risk management, the Popular Bank has an operational risk management policy, an internal control charter, a General Governance Policy of the Business Continuity Plan and an organization of the operational risk function with the objective of converging on the best practices set by the Basel Committee.

The process of identifying operational risks including the implementation of a risk map remains unstable, due to the instability of dedicated human resources (departure of profiles) which leads to changes in approaches. In fact, the first attempt to produce the cartography was launched in 2008, but did not succeed, on the one hand because of the loss of knowledge following the departure of the competences entrusted with this mission, on the other hand, because of the complexity of the chosen model and the lack of adequate profiles.

In terms of quantification, the collection process is in its first phase, and the design conditions of a model are not gathered due to the lack of completeness of the incidents collected and the involvement of operational agents in the collection.
In view of this situation we have tried in this study to implement the approach of risk identification by the development of a cartography of the activity bancassurance and to model the incidents of operational risk generated by this activity despite the absence of an external base. Quantification therefore concerns the bank's internal events.
This point will explain the adjustment and calibration of the standard model with the loss data recorded at the level of bancassurance activity in order to calculate the value at risk at the level of confidence of 99,5% using the Monte Carlo method.

4.1 Description of the sample

Loss data cover a 30-year period from 1 January 1987 to 31 December 2017.

Statistics describing the amounts of bank insurance incidents
We have a sample of the size loss amount equal to 125 achievements. The data range from 3,500 to 35,323,526.06 dhs.

The following table describes the loss data:

Number	Max	min	Mean	variance	standard deviation	median
125	35323.526,06	3.500,00	1.386.076,05	18.391.747.915.819,70	4.288.560,12	172.000,00

We also note that the loss data are far from showing a symmetrical distribution. In fact, the comparison between the mean and the median indicates that the median is much lower than the average. This means that these losses cannot be modelled by the normal distribution.

Therefore, the appropriate distribution must be of positive support with a low probability for the large amount. This feature is verified by some common laws such as the weibull law, the exponential law, the beta law and the lognormal law that we will use in this study.

Statistical description of loss frequencies

For bancassurance we chose the annual period in order to have a sufficient sample for statistical modelling. In fact this type of events is low frequency and disastrous impacts especially for the hijacking, errors such as the omission of the transmission of the underwriting of death insurance all causes that accompanies the granting of credit. The data shall therefore be spread over a period of 30 years, recorded in the database from accounting records and audit and inspection reports.

The following table summarizes the descriptive frequency statistics:

Number	min	max	mean	variance	standard deviation
33	1	23	4.69	46.51	6.82

We note that the average frequency per year is in the order of 4.69 events.

The phenomenon characterised by an average number of occurrences within a given interval (time interval, page number, unit of distance) is often modelled by the Poisson law.

However, the comparison between the mean and the variance also shows that the variance exceeds the mean. This finding also means that a distribution favouring over-dispersion would better model frequencies [4]than the Poisson distribution.

4.2 Parameter estimation and log-normal fit test

The estimation of the parameters of the lognormal distribution and the Poisson distribution respectively is made by the maximum likelihood method, ensuring that the estimator determined is a bias-free estimator.

In this study, we determined only the one-time parameter estimator that will be used to identify the theoretical distributions, the fact that the lognormal distribution is characterized by its mean and its standard deviation and the Poisson distribution is characterized by its mean and the equality of the mean and the standard deviation (equidistribution).

The reliability of the results and the choice of distribution for impact and occurrence depends on the quality of adjustment of the theoretical distributions to the empirical data. As a result, we proceeded with the KS test to test the lognormal distribution and with the Chi square test to test the Poisson distribution.

Once the distributions are tested, we proceed with the calculation of risk capital using simulation functions on EXCEL and applying the algorithm mentioned above.

Parameter estimation (μ.σ)

The lognormal distribution is characterized by the parameters (μ.σ). These parameters are estimated by the maximum likelihood method from which :

$\hat{\mu}=\frac{\sum_1^n Ln(x_i)}{n}$ =12.1891 and $\hat{\sigma}=\sqrt{\frac{\sum_1^n (\ln(x_i)-\hat{\mu})^2}{(n-1)}}$=1.9051

Fit test

The fit test yielded the following results:

Kolmogorov-Smirnov test to one sample		
		ln_amount
N		125
normal parameters[a,b]	Mean	12.1891
	Standard deviation	1.90514
Most extreme differences	Absolute	0.063
	Positive	0.063
	Negative	-0.035
Z of Kolmogorov-Smirnov		0.703
Asymptotic significance (bilateral)		0.706

Based on the KS test for adjusting a log-normal distribution for loss amounts. We note that the P-value of the order of 0.706 > 0.05 therefore we accept the null hypothesis that the variable amount after transformation is distributed according to the log-normal law.

4.3 Parameter Estimation and Poisson Distribution Fit Test

• Estimation of the parameter λ :

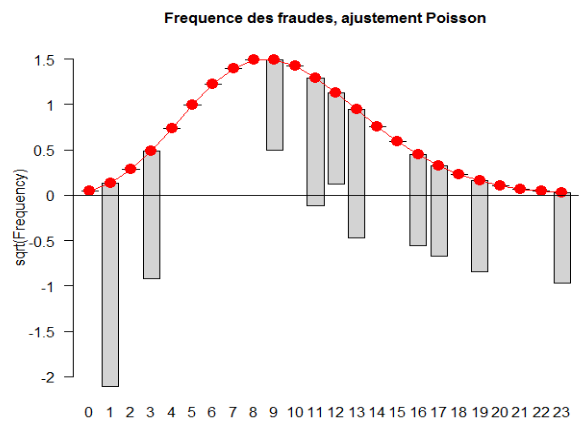
The parameter μ of the fish distribution is estimated by the maximum likelihood method from which :

$\hat{\mu}=\frac{\sum_1^n x_i}{n}$ =4.69

• Adjustment of distribution to data :

By applying the Chi square test on adjustment by a Poisson distribution we find the following results :

```
> summary(ajust)
Goodness-of-fit test for poisson distribution
                 X^2 df P(> X^2)
Pearson 2257.195 22        0
Warning message:
In summary.goodfit(ajust) : Chi-squared
      approximation may be incorrect
```



According to the test of Chi square relating to the adjustment of the Poisson distribution with the amounts of losses. We find that the P-value 0.05 therefore we reject the null hypothesis that the frequency is distributed according to the Poisson law.

This result is confirmed by : Var(X)= 46.51≠ $\bar{X}$=4.69

[4] The negative binomial law called the gamma mixture Poisson law

The frequency data do not adjust with the Poisson law of parameter 4.69, however the standard model provides for the Poisson distribution to model the frequency.

The use of another law such as the negative binomial law (Poisson mix range) can solve this adjustment problem.

4.4 Calculation of operational risk capital

The statistical studies developed earlier have made it possible to calibrate the distributions and to test the adjustment of the distributions adopted with the data of the proven losses in terms of severity and occurrence of occurrence.

We will compare the risk capital determined by the standard model for several thresholds.

Definition of the models:

The model concerned by our study for losses incidents related to bancassurance is the standard model composed of the log-normal distribution for severity and Poisson distribution for frequencies.

Standard "lognormal- poisson" model:

The calibration of the model with bancassurance data showed that:

- Severity is modelled by the lognormal law parameter (12.18; 1.90)
- The frequency is modelled by the Poisson law parameter (4.69)

We note that lognormal law adjusts with empirical data. However, modelling by other laws such as the weibull law, the generalized beta law which may present an alternative to the standard model.

On the other hand, the simple Poisson law does not adjust with empirical frequency data because these observations are not equidistributed. As a result, modelling with negative binomial distribution (gamma Poisson mixture) may present an opportunity to seize.

From the above, we note that the choice of Poisson distribution may affect the estimation of risk capital, which requires the use of the adjustment of the value-at-risk determined either by assigning a scale factor or by increasing the acceptance threshold.

CaR determination by standard model

The calculation of risk capital is done in accordance with the algorithm cited in the study approach. To determine risk capital, we will calculate the annual aggregate loss generated by the misappropriations, noted S_da defined by :

$S_{da} = \sum_1^{N(t)} X_i$

With:

- N(t) is a random Poisson variable represents the annual frequency and
- X_iis a lognormal random variable showing the claims amounts.

Simulation of variables :

The simulation of random variables is done by the Excel tool using the predefined functions :

The Poisson law parameter λ =4.69 :

The simulation of the Poisson law is given by the function «CRITBINOM», by bringing the Poisson law closer by the binomial by making $\frac{4.69}{n}$ tend towards 0, by increasing n~ 20000.

In fact the function **CRITBINOM (20000 ;$\frac{4.69}{20000}$; alea())** allows to simulate the variables of the Poisson parameter λ=4.69.

The lognormal law :

The function : LOGINV (alea () ; 12.18 ; 1.90) allows to simulate the variables of the Poisson law parameters (12.18; 1.90).

Determination of risk capital at the 95% threshold. 99% and 99.9%

The simulation is done in two stages, which allowed us to determine the results of the following table:

- Simulation of annual loss by function: $S_{da} = \sum_1^{N(t)} X_i$ with N(t) is a random Poisson variable and $X_i$is a lognormal random variable ;
- Repeat of the previous step 30,000 times to calculate Risk Capital.

This approach resulted in the following results :

Threshold	95%	99%	99.9%
Risk capital	17.546.340	25.499.500	29.953.855

3.5 Calculation of operational risk

The operational risk incurred by the bank is determined by the following formula:

*OR = CAR*12.5*

With :
OR : operational risk
CAR : risk capital

Consequently, the operational risk by confidence threshold is summarised in the following table:

Threshold	95%	99%	99.9%
Risk capital	219 329 250,00	318 743 750,00	374 423 187,50

5. Conclusion

The quantification of risks and the allocation of own funds remain the most complex phase in the operational risk management process, as a result of the regulatory constraints specific to each calculation approach.

This complexity has been of concern to professionals in the field as well as academics whose objective is to implement a method that meets regulatory constraints while allowing better optimization of the measurement of own funds to be allocated.

In this work, we have shown the sensitivity of the LDA method to the quality of the data collected and to the choice of distributions to be used especially for the frequency of occurrence which may lead to the overestimation of risk capital in a very significant way.

It should be noted that the LDA method is based on strong assumptions which may overestimate or underestimate risk capital, in particular those concerning the estimation of future loss by past loss, which represents a neglect of the effect of the control environment and organizational changes.

As regards the choice of model, our concern was to have the best fit with the loss data in terms of occurrence and severity based on the statistical tests of suitability in the objective of having a model that allows to generate losses of the same profile l that have already occurred.

Analysis of the characteristics of the lognormal law, including the shape of the tail of the distribution leads us to suppose that the results obtained by the simulation of the values of the lognormal law favour the large (exponential) values, and consequently the tendency of the standard model to overestimate the VAR.

In order to correct this bias in the simulation and calculation of the value at risk, we consider it essential to include expert opinions in the LDA model for two reasons:

- Consider risks that occur at very low levels;
- Correct the simulation bias by estimating the effectiveness of the control device and its ability to reduce the simulated gross impact by the Monte Carlo method.

This approach to incorporate expert advice should be applied to each risk event using the operational risk mapping.

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