



Operational risk: scaling the severity of external operational risk data

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Introduction

The Basel II framework in operational risk has brought about a huge trend of research over the past years, leading to more effective risk management practices, better assessment of risks and more accurate modelling. However in many respects, operational risk frameworks within banks are far from mature and will require a significant period of time before being entirely satisfactory.

The last paper released by the Basel Committee on Banking Supervision (2009) clearly puts in evidence that a lot remains to be done. Regarding operational risk, there is no consensus as at now about the right balance between the four core requirements specified by supervisors: internal data, external data, scenario analysis, business environment and internal control factors (BEICFs). All banks do use these four elements, if only because this is a strong regulatory requirement, but they do so in proportions which differ significantly between institutions. Accordingly, the last Basel document on banks' practices states that *"one of the major distinguishing features of operational risk models is how the models combine internal loss data, external data, scenario analysis and business environment and internal control factors (BEICFs)"*. ('Observed range of practice in key elements of Advanced Measurement Approaches (AMA)', 2009)

This lack of homogeneity between banks' actual practices is admittedly an indicator that the practice around operational risk is not mature yet. More importantly, it has undoubtedly strong impacts on capital computation. Heterogeneous practices are likely to generate variability in capital requirements. As a result, one may suspect that two banks having different methodologies but otherwise identical risk and data would likely end up with highly different figures for the amount of regulatory capital to be put aside for operational risks, which raises significant concerns about the overall capital charge of the banking industry and its adequacy with the actual operational risk profile (not to mention potential competitive distortions within the industry).

Quantification and modelling are at the crossroads of the four core elements. Based primarily on internal loss data – for both frequency and severity modelling – quantification has also to be linked to external loss data, scenario analysis and BEICFs. According to the last Basel document, *"the combination and weighting of individual elements vary widely across banks. Some banks base their operational risk capital estimate largely – or even solely – on scenario analysis, and incorporate internal and external data only indirectly as inputs to the scenario elicitation process. Other banks rely heavily on internal loss data, using external data and scenario analysis only where there are gaps in their own loss experience. Others use internal loss data to model the frequency of operational risk losses and external data to model loss severity, especially in the tail. Most banks, however, incorporate more than one element directly in their AMA model, and some incorporate all four, albeit with varying weights."* ('Observed range of practice in key elements of Advanced Measurement Approaches (AMA)' 2009)

Our view in this paper is that such heterogeneous practices reflect insufficient methodological maturity and our aim is focused on some methodological improvements for a better combination of these four core elements.

It has been long recognized that capital figures are very sensitive to the underlying loss data used for quantification. The lack of data and most of the time their poor quality has been a challenge



for financial institutions. As an example, modelling low frequency – high severity risks should be preferably anchored on external loss data (since internal loss data is likely missing) but no methodology exists for doing that properly.

Among the many issues encountered in related literature, the following ones may be mentioned:

- The different threshold levels below which internal and external loss data are not reported (and sometimes the lack of a known threshold level)
- The different granularity levels in data collection and the absence of an agreed definition of what net and gross losses are. As an example, there is no general agreement on whether loss amounts should include actual and expected recoveries, collection charges, etc. and also which valuation date is the most relevant.
- And above all, the counterintuitive (and probably unreasonable) idea of mixing directly internal data with external data coming from third-parties whose asset or income size, geographic location and other features are entirely different.

This paper aims at developing an adequate and robust methodology for addressing this last issue, which is by far the most difficult one, considering that issues surrounding threshold differences have already been given an appropriate methodological solution (see for example Baud, Frachot and Roncalli (2003) and Frachot, Moudoulaud and Roncalli (2003)).

Our methodology provides a consistent process for adjusting, scaling and filtering external loss data in order to make them relevant with bank's own features (such as asset / income size, geographical location etc.) and therefore relevant for severity calibration and capital quantification. We detail how adjusting / scaling / filtering can be conducted practically and numerically using Aon OpBase™ database, which is managed by Aon as part of its insurance broking activity. Indeed, OpBase™ records loss data experienced by insurance contracts managed by Aon. Please refer to page 8 for a description of this loss database.

In this paper, we first provide background information and explain how scaling issues appear in quantification processes. We then describe our approach and present the numerical results of our study. Finally, we discuss some applications of our work.



II. Operational risk modelling with external data

We mainly focus on the so-called Advanced Measurement Approaches (AMA) and, in particular, on Loss Distribution Approaches (LDA), whereby capital figures are derived from a loss distribution percentile (at a 99.9 % level). According to this approach, the loss distribution is the resulting distribution of two random processes, namely loss frequency and loss severity.

This approach is now by far the most widely used among AMA banks although they diverge significantly in the way they implement it, for example with respect to the model granularity, underlying distributional assumptions, data adjustment, etc. According to the last Basel document, 'Results from the 2008 Loss Data Collection Exercise for Operational Risk' (2009) frequency is modelled through a Poisson process in most banks and loss severity is often assumed to be either log-normal or Weibull.

Because of the paucity of internal data and their poor quality, banks often struggle to implement LDA in a sound and statistically satisfactory way. Some shortcuts have to be taken to adjust parameters, as some of them cannot be directly derived from a rigorous statistical procedure based on a sufficient quantity of good quality data. In practice, banks have to refer to scenario analysis, external data and BEICFs to adjust or even evaluate the severity / frequency mean or any other related parameters.

Should banks have a consistent way to merge internal and external loss data, they would be able to use rigorous statistical procedure one step further and thus avoid this sort of arbitrary and judgemental inference which is hardly justifiable and which generates large variability among banks capital calculations.

II.1. Mixing internal and external data

External loss data may be used for frequency calibration or severity or both. Most of the time, relying on external loss data for frequency assessment constitutes a sensitive issue and would require judgemental inputs from experts as no external database can ensure that its contributors actually feed the database in the same way. Threshold effects (of the data collection process), size-related frequency etc. may distort the overall quality and reliability of any dataset as it is highly difficult to overcome these biases through a statistical methodology.

On the other hand, even though these very same biases exist in severity calibration based upon external data, it is much easier to filter them out and end up with unbiased estimators of severity parameters. Regarding threshold heterogeneity, Baud, Frachot and Roncalli (2003) have shown that severity parameters can be consistently estimated on a set of loss data coming from collection processes differing with respect to threshold.

Regarding the severity scaling of the operation losses some research has been conducted on the subject. The first studies considered the size of the bank as the most important scaling factor for the operational risk losses.

J. Shih, A. Samad-Khan and P. Medapa (2000) test a relationship considering the operational loss



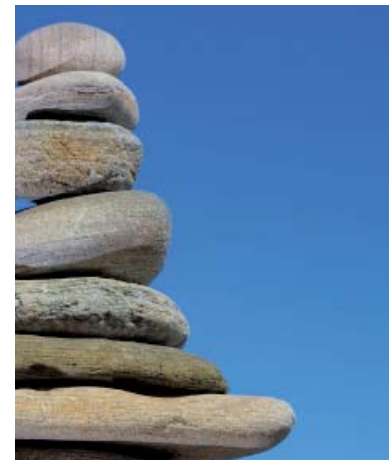
amount as a result of multiplying a power term of the institution size and another residual term not explained by any fluctuations in size. The numerical results show that the size explains only a small part (approximately 5 %) of loss variability.

T. Hartung (2004) proposes a normalization formula that would allow scaling an external loss to an equivalent one for a reference bank, using a scaling parameter and 2 adjustment factors.

H.S. Na (2004) suggests another approach supposing that the loss due to the operational risk for a bank can be thought as caused by two components: the 'common' component, which is the same for all institutions and the 'idiosyncratic' component, specific to each institution. The 'idiosyncratic' component is a function of the bank's size.

Building on this study, H. Dahren (2006) suggests including other factors than the size of the bank in the idiosyncratic component.

In the same line of reasoning, we try here to set up a rigorous methodology for adjusting severity parameters when size-related, asset-related or geographical-related effects are nested in the collection process. Basically, we link the severity parameters to observable variables and we calibrate this link by a maximum likelihood method.



More specifically, our key assumption is that both external and internal loss data are log-normally distributed but differ from one another by their parameters. Moreover, these parameters are assumed to depend on the characteristics of the banks the loss data come from.

Formally, assuming that the severity distribution for a particular risk type is log-normal with parameters μ and σ^4 , then our model states that:

$$\mu(X) = \alpha_1 \ln(\text{Gross_Income}) + \alpha_2 \ln(\text{Empl_Count}) + \alpha_3 \text{EU} + \alpha_4 \text{North_Am} + \alpha_5$$

and:

$$\ln(\sigma^2(X)) = \alpha_6 \ln(\text{Gross_Income}) + \alpha_7 \ln(\text{Empl_Count}) + \alpha_8 \text{EU} + \alpha_9 \text{North_Am} + \alpha_{10}$$

where Gross_Income, Empl_Count, EU, North_Am stand respectively for the bank's Gross income, its number of employees and two dummy variables equal to 1 (or 0 otherwise) if the loss has taken place in the European Union or in the North America (mainly United States and Canada)⁵.

In short, our model assumes that the heterogeneity between external and internal loss data does not come from different types of distribution but only from different specifications within the same class of distribution (i.e. log-normal distributions). It may seem to lack sufficient generality but one must have in mind that assuming otherwise (i.e. external and internal loss data come from two different classes of distribution), would lead to the conclusion that mixing external and internal data is fundamentally flawed, theoretically and practically.

⁽⁴⁾ We retain the definition of the log-normal distribution according to which its parameters are the mean and the standard deviation of the corresponding normal distribution.

⁽⁵⁾ 3 areas are considered here: North America, EU and Non-North America and Non-EU (mainly the Asian area).



II.2. External data and scaling issues

For practical use, our model must be transformed into an easy rule of thumb for turning external loss data into “internally-consistent” data, that is loss data which are consistent with internal loss data (and therefore which can be safely mixed). Deriving a scaling rule offers the key for doing that.

When mixing internal and external loss data for the purpose of severity calibration, one must be aware of the strong link between scaling and distributional assumption. First, scaling loss data with respect to whatever variable cannot be done without related assumption on the severity distribution. Scaling process and distributional assumption go hand in hand and can be neither discussed nor modelled separately. The reason is that probability distributions are generally not invariant with respect to scaling adjustment. As a straightforward example, linear scaling of a loss data (e.g. $a \times L + b$) cannot be consistent with log-normal distributional assumption, as the unscaled loss data (here L) and the scaled one ($a \times L + b$) cannot be both simultaneously log-normally distributed. If the former is log-normal, then the latter is not.

As a consequence, any scaling function must be consistent with the distributional assumptions made for both internal and external data. If both internal and external loss data are assumed to be log-normal, then applying a linear scaling function on external data (in order to be mixed with internal loss data) is inconsistent and will result subsequently in spurious severity calibration. Indeed the only functions that maintain log-normality are of the following type:

$$h(y) = b \cdot y^a$$

Let us now assume that:

- The characteristics of a bank are a vector X
- Internal losses follow a log-normal distribution of parameters μ and σ
- μ and σ are functions of X (denoted $\mu(X)$ and $\sigma(X)$, see previous sections for specification).

We consider a reference bank where X_0 , μ_0 and σ_0 denote respectively its characteristics and its parameters. Here “internal loss data” refer to the losses coming from this reference bank while “external loss data” refer to losses generated by any other bank whose characteristics are denoted by X .

Accordingly, any loss L from a bank of characteristics X should be scaled so that this scaled loss L^* follows the same distribution as any internal loss. Denoting h the scaling function (with $h(y) = b \cdot y^a$), the scaled loss L^* is given by:

$$L^* = h(L) = b \cdot L^a$$

or:

$$\ln(L^*) = \ln(b) + a \cdot \ln(L)$$

Therefore it is straightforward that if L is log-normally distributed according to $\mu(X)$ and $\sigma(X)$, then the scaled loss L^* is log-normally distributed according to $\mu(X_0)$ and $\sigma(X_0)$, if and only if the scaling adjustment is performed according to:

$$a = \frac{\sigma(X_0)}{\sigma(X)} \qquad b = \exp \left[\mu(X_0) - \mu(X) \cdot \frac{\sigma(X_0)}{\sigma(X)} \right]$$



III. Scaling adjustment in practice

III.1. OpBase™⁶

OpBase™ is an operational risk loss event database containing quantitative and qualitative information on more than 16,500 losses and incidents experienced by more than 1,600 financial institutions worldwide.

OpBase™ contains two sources of data:

- Proprietary loss data that Aon was able to gather through its broking activity
- Loss information sourced from the public domain (Publicly Known Matters).

Proprietary loss data

This part of the database contains loss information related to approximately 13,000 incidents. The loss history used for this study spans a period from 1978 to 2008. Loss amounts range from USD 4 to USD 798m.

Publicly Known Matters

Sources for this information include press publications, court proceedings, trade and business journals, Internet, newswire services, regulatory bodies, etc.

Our study was based on the proprietary loss data only, as we consider that the collection thresholds are more homogenous and of a lower level than for the public data.

For each entry, bank's characteristics are recorded so that each loss data can be linked to its corresponding vector of bank's characteristics X governing the mean and standard deviation.

III.2. Maximum Likelihood estimation

For every type of operational risk defined in Basel II, the relationship between the distribution parameters and the characteristics of a chosen bank is calibrated by the method of the maximum likelihood.

The maximum likelihood estimate $\hat{\alpha} = (\hat{\alpha}_1 \dots \hat{\alpha}_{10})$ of the coefficient linking the parameters of the log-normal distribution to the characteristics of the bank is the solution of the optimisation problem:

$$\begin{aligned}
 \hat{\alpha} &= (\hat{\alpha}_1 \dots \hat{\alpha}_{10}) = \underset{\alpha = \alpha_1 \dots \alpha_{10}}{\text{Arg max}} L_n(\alpha_1 \dots \alpha_{10}) \\
 &= \underset{\alpha = \alpha_1 \dots \alpha_{10}}{\text{Arg max}} \prod_{i=1}^n f(Y_i) = \underset{\alpha = \alpha_1 \dots \alpha_{10}}{\text{Arg max}} \left(\sum_{i=1}^n \ln(f(Y_i)) \right) \\
 &= \underset{\alpha = \alpha_1 \dots \alpha_{10}}{\text{Arg max}} \sum_{i=1}^n \ln \left[\frac{1}{Y_i} \frac{1}{\sigma(X_i, \alpha) \sqrt{2\pi}} \times \exp \left(-\frac{(\ln Y_i - \mu(X_i, \alpha))^2}{2\sigma^2(X_i, \alpha)} \right) \right] \\
 &= \underset{\alpha = \alpha_1 \dots \alpha_{10}}{\text{Arg max}} \sum_{i=1}^n \left[-\ln \sigma(X_i, \alpha) - \frac{1}{2} \frac{(\ln Y_i - \mu(X_i, \alpha))^2}{\sigma^2(X_i, \alpha)} \right]
 \end{aligned}$$

⁽⁶⁾The description of OpBase™ included in this document relates to the database as it stood at the time of our analysis.



Where:

- $L_n(\alpha_1 \dots \alpha_{10})$ is the likelihood function
- Y_i is the loss of the financial institution i
- X_i is the vector of the characteristics of the financial institution i

It is not easy to find the solution of this optimisation problem with 10 variables, as a requirement for most of the optimisation algorithms to give good results is to initialize them with a point near the solution.

We have used the algorithm of Nelder – Mead with a starting point obtained by the ordinary least squares estimator ($\alpha_1 \dots \alpha_{10}$)

$$(\alpha'_1, \dots, \alpha'_5) = \min_{\alpha_1, \dots, \alpha_5} \left\| \ln(Y_i) - (\alpha_1 \times \ln(\text{Gross_Income}) + \alpha_2 \times \ln(\text{Empl_Count}) + \alpha_3 \times \text{EU} + \alpha_4 \times \text{North_Am} + \alpha_5) \right\|$$

$$(\alpha'_6, \dots, \alpha'_{10}) = \min_{\alpha_6, \dots, \alpha_{10}} \left\| \ln \left[\ln(Y_i) - \mu'(X_i) \right]^2 - (\alpha_6 \times \ln(\text{Gross_Income}) + \alpha_7 \times \ln(\text{Empl_Count}) + \alpha_8 \times \text{EU} + \alpha_9 \times \text{North_Am} + \alpha_{10}) \right\|$$

Where:

$\|\cdot\|$ is the Euclidean norm

and

$$\mu'(X_i) = \alpha'_6 \times \ln(\text{Gross_Income}) + \alpha'_7 \times \ln(\text{Empl_Count}) + \alpha'_8 \times \text{EU} + \alpha'_9 \times \text{North_Am} + \alpha'_{10}$$

By using the likelihood-ratio test we study the statistical significance of the variables of the model and we select the characteristics of the bank which explain the severity of the operational losses for the Basel II risk types.

III.3. Main results

The coefficients alpha linking the characteristics of the bank with the parameters of the severity distribution for each type of risk resulting from the maximum likelihood estimation and the likelihood ratio test are shown in the table below⁽⁷⁾.

			CP&BP	IF	EF	ED&PM	EP&WS	DPA
mu(X)	Gross Income	alpha 1	0,76	0,28	0	0	0	0,31
	Headcounts	alpha 2	-0,49	0	0	0,23	0,09	0
	Europe	alpha 3	0	0	-1,46	0	-0,86	-4,53
	North America	alpha 4	0	0	-0,73	-1,40	1,11	-1,94
	Cnst	alpha 5	9,93	11,18	11,40	8,95	6,03	9,84
ln[sigma(X)]	Gross Income	alpha 6	0,27	0,10	0,12	0	0	0
	Headcounts	alpha 7	-0,14	0	0	0	0,08	0
	Europe	alpha 8	0	1,01	0,47	0	0,38	0
	North America	alpha 9	0,68	0,57	1,23	0	1,03	0
	Cnst	alpha 10	0	0	-0,58	1,47	0,59	1,13

⁽⁷⁾ The type of risk «Business disruption and systems failures» is not included in the analysis due to the small number of observations linked to this type of risk in Opbase.



Where the risk types are named as:

- CP&BP: Clients products & business practices
- IF: Internal fraud
- EF: External fraud
- ED&PM: Execution delivery & process management
- EP&WS: Employment practices & workplace safety
- DPA: Damage to physical assets

These numerical results are very interesting. To our knowledge, it is the first time that the mean and variability of loss severity have been related numerically to gross income, headcount or loss location. Even though these results are to be interpreted carefully, it is nonetheless worth mentioning that:

- The mean of the loss severity and its variability are positively correlated to gross income⁽⁸⁾. It does not come as a surprise that operational risk losses are larger in large banks but it is less straightforward that they seem to be more dispersed.
- Headcount is not a relevant variable for Internal Fraud, External Fraud or Damage to Physical assets.
- Employment practices generate higher losses in North America than in Europe, reflecting perhaps differences in legal environment.
- Etc.

We will leave it to the reader to see whether these numerical results match his or her own intuition and experience.

The scaling function for the reference bank with given characteristics is thus entirely defined and we apply it to the external loss data. For example, when applying our calibration on a (fictitious) reference bank whose characteristics are:

Gross income: \$M 6 333
 Headcounts: 38 128
 Geographical region: North America

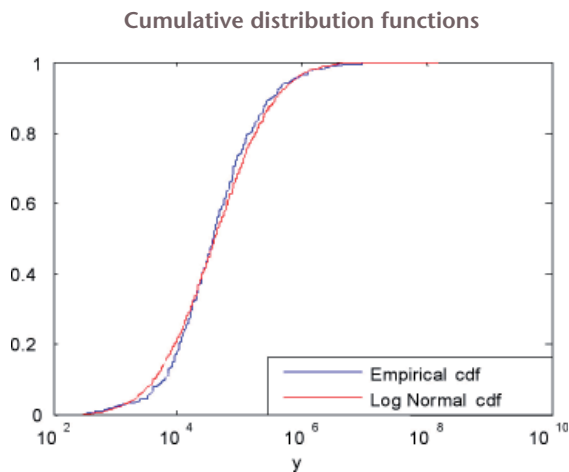
we obtain the following parameters:

	CP&BP	IF	EF	ED&PM	EP&WS	DPA
μ	11,41	13,64	10,67	10,36	8,12	10,61
σ	2,16	2,04	2,33	2,37	3,40	1,76

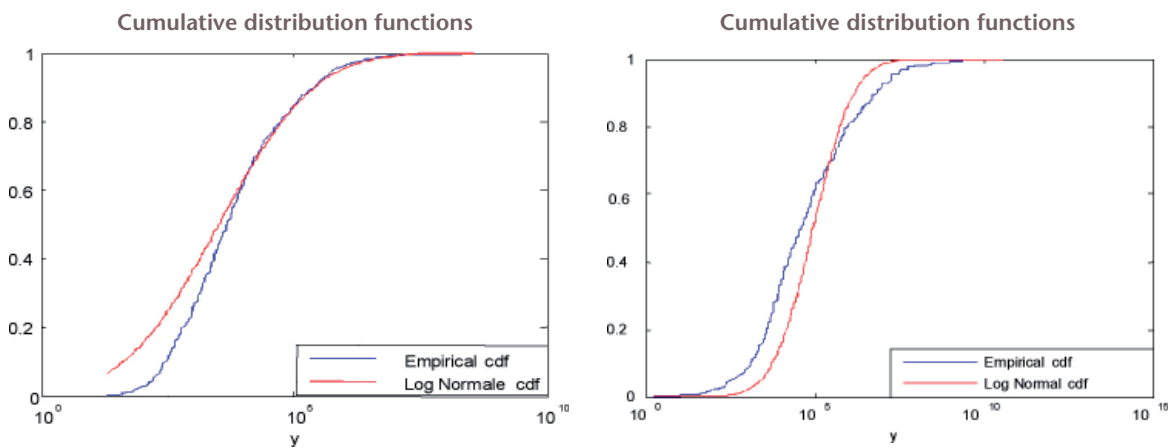
⁽⁸⁾ The mean $E(Y)$ and the volatility $V(Y)$ of the loss distribution are linked to μ and σ by the following relationships:
 $E(Y) = \exp(\mu + \sigma^2/2)$ and $V(Y) = [\exp(\sigma^2) - 1] \cdot \exp(2\mu + \sigma^2)$.



Besides, the statistical test of Kolmogorov-Smirnov (K-S) is used to test the validity of the assumption of log-normality. For the risk entities «Internal Fraud», «Execution, delivery and processes management» and «Damages to physical assets» the log-normality assumption is accepted by the K-S test at a 95% confidence level. This result was also confirmed by graphic tests. We present below the graph comparing the empirical and theoretical cumulative distribution for the event type “Damages to physical assets”.



For the event type «Employment practices and workplace safety», the log-normal distribution fits well the scaled data, beyond a given threshold as shown in the following graph (to the left):



For the two other event types “Clients, products and business practice” and “External fraud”, the assumption of log-normality is rejected by the test K-S at a 95% confidence level. We present below the graph comparing the empirical and theoretical distribution for the type of risk “Clients, products and business practices”.



IV.Applications

This paper has developed a way to extract relevant information from a set of external loss data, provided that this data is adjusted for each bank's specific features. This methodology may be used in numerous ways in practice: improve and enhance severity accuracy by calibrating severity curve on a global set of internal loss data and properly-scaled external losses; use the adjusted OpBase™ severity curve as a benchmark for a bank's own severity curve, etc.

IV.1. Framework and methodology to mix internal and external data

We believe the previous sections provide a sound framework and a consistent methodology to model severity distributions on the basis of internal and external data. Whilst our analytical study provided interesting results on the basis of a significant amount of data, it would be interesting to follow the methodology described above to model severity distributions for a financial institution, using both internal and external data.

However, this methodology can be quite time-consuming. Once a thorough analysis has been carried out and the α_i estimated, it can be decided, whenever new data is available, to rescale the external data using the scaling function defined on page 7⁽⁹⁾, to mix it with the internal data and to fit a new distribution on the new dataset.

Note however that these approaches require access to detailed external data (not only historical losses, but also the institutions' characteristics). Most institutions rely on external providers to get external data. These providers could use the methodology described in this article to define and parameterise a scaling function and scale the historical losses for each client on the basis of its characteristics.

IV.2. Consistency with the Basel II Basic and Standard Approaches

We have also used the adjusted OpBase™ severity curve as a benchmark to challenge the Basic and Standard Approaches. In these two approaches, capital requirements are calculated as a proportion of a bank's gross income. Though it is very easy-to-implement, it is nonetheless essential to prove that this back-of-the-envelope formula provides banks with the exact level of magnitude for capital figures. As an example, we computed the implied frequency necessary to make our OpBase™ severity curve and the Basel II proportion coefficients both consistent. In some sense, we reverse-engineer the Basel II Basic and Standard approaches to extract the implied frequency distribution, assuming that these two approaches give the right level of magnitude and that the OpBase™ severity distribution is a correct benchmark (when adjusted for income and geographical-related effects).

Though more in-depth analysis would be necessary, we suspect that Basic and Standard approaches could be improved significantly. Indeed, the implied frequency obtained by reverse-engineering does not seem always consistent with common intuition about the annual rate at which certain event types may occur.



The results of the reverse-engineering estimation for our reference bank are given in the following table:

Type of risk	Estimated frequency
CP&BP	27
IF	6
EF	39
ED&PM	45
EP&WS	26
DPA	2

The results of this application have to be taken with great caution, as the frequency benchmarks may not be fully consistent with our severity distributions. In particular, the frequency data relates to all losses, whereas our loss data is biased by reporting thresholds. As a consequence, we may be too conservative when combining our loss distributions with frequency distributions derived from the Basel Committee document “Results from 2008 Loss Data Collection Exercise for Operational Risk”.

Generally speaking, we would recommend using internal data to model frequency distribution. In addition, in order to limit the bias due to reporting thresholds, severity distributions could be split in two parts: internal data could be used to model the distribution below a given threshold, while the distribution above this value would be modelled using internal and external data.

V. Conclusion

Further research should be directed to refine parameter estimates along with the accumulation of more loss data. We hope that our methodology combined with other methodological improvements and a greater number of data will achieve soon a wider consensus on capital quantification and a more balanced use of the four core elements demanded by Basel regulations.



Disclaimer

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References

Basel Committee on Banking Supervision (2009) 'Observed range of practice in key elements of Advanced Measurement Approaches (AMA)', July 2009, available at: <http://www.bis.org/publ/bcbs131.pdf?noframes=1>

Basel Committee (2009), 'Results from the 2008 Loss Data Collection Exercise for Operational Risk', July 2009, available at <http://www.bis.org/publ/bcbs160a.pdf>

N. Baud, A. Frachot, T. Roncalli (2003) 'How to avoid overestimating capital charge for operational risk?', February 2003, Operational Risk

H. Dahren (2006) 'La quantification du risque opérationnel des institutions bancaires'

A. Frachot, O. Moudoulaud, T. Roncalli (2003) 'Loss Distribution Approach in practice', December 2003, in The Basel Handbook: A Guide for Financial Practitioners

T. Hartung (2004) 'Operational risks: Modelling and quantifying the impact of insurance solutions' Working paper, Institute of Risk Management and Insurance Industry, Ludwig-Maximilians-University Munich, Germany

H.S. Na (2004) 'Analysing and scaling operational risk loss data', Master Thesis, Erasmus, University Rotterdam, Netherlands

J. Shih, A. Samad-Khan, P. Medapa (2000), 'Is the size of a operational loss related to a firm size?' Operational Risk Magazine, January 2000



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