Quantification of Operational Risk

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I. INTRODUCTION

Until recently, the banking industry used to devote few resources to the management of operational risks. These risks were considered to be qualitative rather than quantitative. In its 1998 paper on operational risk management, the Basle Committee stated that most big losses in the banking industry resulted from internal control weaknesses or lack of compliance with existing internal control procedures. Thus, improving the quality of management seemed the best way to reduce operational risks, while offering the added benefit of leaving risk managers free to concentrate on controlling market and credit risks.

However, in its June 1999 consultative paper ?A New Capital Adequacy Framework?, the Basle Committee on Banking Supervision proposed to introduce a capital charge for operational risks. Moreover, risk adjusted performance measures (RAPM) are increasingly being used by senior managers in their decision-making process. To estimate both the most accurate measures and capital charges requires quantifying operational risks.

This article will mainly address the practices and techniques currently employed in quantifying operational risks, adding a brief definition of operational risk and the most up-to-date methods of identifying and managing such risks.

II. DEFINITION

There is no consensus on the definition of operational risk. Some banks define it as every kind of risk other than market and credit risk. Others define operational risk as an (un)expected loss resulting from human error, fraud, process failure, technology breakdown or external factors. All businesses have risks and small operational losses are usually expected. Some of these losses can be quantified. Sometimes they are even anticipated in the pricing of specific products, as in the fees and commissions of credit cards. In the case of credit cards, operational losses can arise from billing errors, overcharging or forgery.

III. IDENTIFICATION

Before quantifying operational risks, they must first be identified. One way of doing this is to ask each manager to outline his or her ten biggest operational risks. The operational risk manager then groups these risks into categories of operational risk similar to the following:

- **Information Technology Risk**
  System failure, Internet virus, inaccurate data, poor quality lines of communication?

- **Human Resources Risk**
  Recruitment procedures, incompetent staff, holiday policy?

- **Loss to Assets Risk**
  Risk that damages assets could interrupt the business. This damage could be due to fire, flood or earthquake.

- **Relationship Risk**
  Changes in regulatory requirements, claims, customer satisfaction, lawsuits?

These risks are either assumed by the company or avoided. For instance, a company could avoid the Internet virus risk by simply forbidding its employees to access the Internet. On the other hand, the management could assume the operational risk. In this case, the operational risk manager must then determine the amount of capital required to protect the company against this particular risk by quantifying the assumed risk. The quantification of operational risk is also important for running cost-benefit analyses and estimating the impact of management actions.

IV. QUANTIFICATION

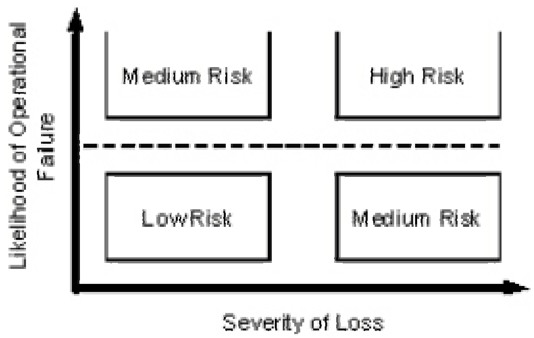
The operational risk manager is not only interested in the categorization of the operational risk, but also in the frequency and severity of the operational losses. Quantitative specialists are aware that some operational risks, such as reputation risk, cannot be quantified. Therefore, in order to quantify operational risk, the relevant specialists must find the risk involved in the list of categories provided by the operational risk manager. Their focus will only be on operational risks that might result in a monetary loss.

IV.1. Frequency and Severity

For each selected risk category the number of losses (frequency) and the size of the losses (severity) occurring over a specific time period are noted. If the company has an advanced database infrastructure, these losses may already be documented in a data warehouse. For each category, the risk is mapped as shown in figure 1.

Figure 1

The Mapping of Operational Risk

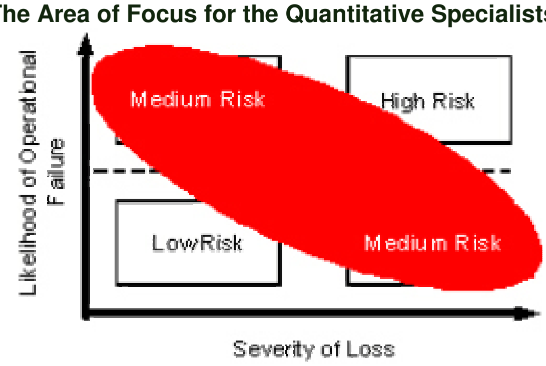


- **Low Frequency Low Severity**
  The operational risk manager will probably not allocate resources to quantify these low impact risks.

- **High Frequency High Severity**
  If the operational risk manager encounters such high impact risks, they should be reported immediately to the top management. Something is obviously going wrong in the company.

Figure 2

The Area of Focus for the Quantitative Specialists



- **High Frequency Low Severity and Low Frequency High Severity**
  The area shaded in figure 2 is the area of focus for quantitative specialists. These specialists might have some difficulty obtaining sufficient internal data on low frequency high severity losses. On the other hand, low impact high frequency operational losses should be well documented within the company and hence allow the quantitative specialists to use their whole set of statistical tools.

IV.2. Where Statistics Come Into Play

Statistics provide tools to help choices to be made when the information available is incomplete. Using statistics to analyse the data on operational losses, the quantitative specialists can produce statements such as:

- There is a 95% chance that a certain bank will be losing less than 10

Million Currency Units due to late settlement during the whole of the next year.

The measure of how much money a bank with a given level of statistical confidence might lose over a particular period is called the value at risk (VaR). This number is not easily obtainable. The difficulty lies in finding the right probability distribution. The quantitative specialists concerned must first determine a distribution that is well suited to the frequency of a particular category of operational loss. A second distribution then models the severity of the loss in question. Finally, an aggregate distribution can be extrapolated by combining the frequency and severity distributions.
The Poisson distribution can be used to establish the frequency distribution. A common application of the Poisson distribution is to predict the number of events occurring over a specific period of time, such as the number of operational losses occurring in one year.

Formula 1

The Poisson Density Function

$$f(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}$$

where ? is the expected number of operational losses occurrence.
As regards the severity distribution, the Weibull distribution might be a good choice. It is often used in reliability analysis. In this case, instead of estimating ?how long?, the distribution formula is used to assess ?how much?.

Formula 2

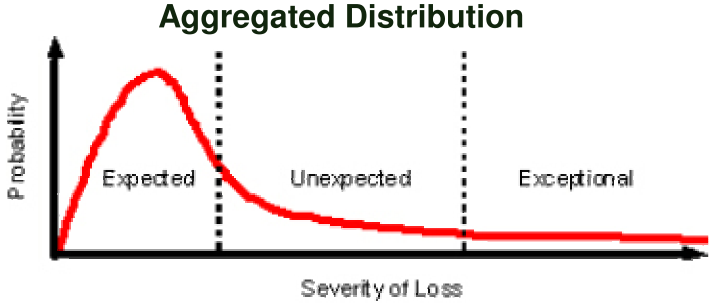
The Weibull Density Function

$$f(x) = \left(\frac{\alpha}{\beta}\right)\left(\frac{x-\mu}{\beta}\right)^{\alpha-1} \exp\left(\frac{\mu-x}{\beta}\right)^{\alpha}$$

where a,□ and ? represent the parameters of shape, scale and position. These last parameters are estimated through the process called distribution or curve fitting.
However, the Weibull distribution does not fit well with large losses. Quantitative specialists therefore truncate the Weibull distribution over a specific high threshold and select another distribution formula to model the tail. Extreme Value Theory (EVT) is an approach to modelling tails distribution and may be approximated by a generalized Pareto distribution (1).

Figure 3

Aggregated Distribution



Monte Carlo simulation (2) or Fast Fourier Transform (FFT) (3) can provide the aggregated distribution to calculate the operational VaR. This type of distribution could resemble the distribution represented in figure 3, with the following subdivisions:

- **Expected Loss or Process Risks**

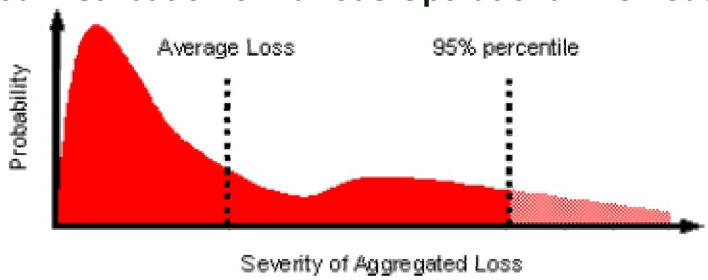
Loss resulting from process failure.

- **Unexpected Loss or Control Risks**
  Loss resulting from internal control weaknesses.

- **Exceptional Loss or Integrity Risks**
  Loss resulting from disaster, fraud or major system failure, and which might affect the integrity of the company.

Figure 4

Aggregated Distribution of Various Operational Risk Categories



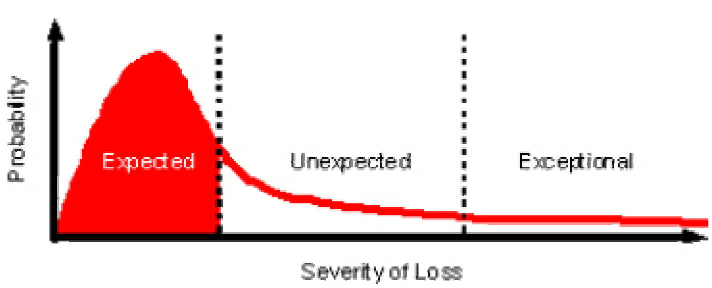
As for market VaR, it is quite complicated to calculate the operational VaR of a combination of several categories of operational risk. This calculation depends on the degree of dependency among these operational risk categories. The quantitative specialists can choose a conservative approach by just totalling the operational VaR of each selected category. When there are sufficient data available, the aggregated operational VaR is reduced by assessing the degree of dependency based on historical data. The 95% percentile in figure 4 represents the operational VaR with a confidence of 95%. An operational risk manager who finds this last figure too high could then discover which actions might reduce it.

IV.3. Cause and Effect

In order to mitigate operational losses, the operational risk manager has to identify the exposure drivers and quantify their influence on the frequency or severity of such losses. Quantitative specialists need a considerable amount of data to identify these drivers and will therefore focus their research on the expected operational loss category (figure 5).

Figure 5

Area of Focus for Identifying the Exposure Drivers



There are several techniques currently used to link causes to events:

- **Neural Network**
  The neural network method has already proved itself in industry and especially in aeronautics. It will most probably become popular in a few years? time among financial institutions as well. A neural network is a massive parallel-distributed processor that has a natural propensity for

storing empirical knowledge and making it available for use (4). For instance, neural networks with statistical learning functions are able to elaborate forecasting models in the field of reliability.

- **Multiple Linear Regression**
  This technique has stood the test of time, and has been popular over the last fifty years among econometricians. It is used, for instance, to estimate the impact of overtime on the frequency or severity of operational losses.

Table 1

Example of Multiple Linear Regression

Month	Number of Operational Losses	Amount of Losses	Overtime in Hours	Number of Transactions	Number of System Failures
January	84	1,600,000	80	1230	41
February	93	1,893,452	110	1280	43
March	68	1,356,318	50	812	35
April	110	2,321,725	160	1523	62
May	49	1,000,987	14	710	18
June	151	2,300,012	218	1510	83

By running the multiple regression analysis, we obtain the following monthly estimations:

[N? Operational Losses] = 40.73 + 0.34 [Overtime] ? 0.01 [N? Transactions] + ?? 0.57?[N??System Failures]

[Amount Losses] = 486,591 + 4,401 [Overtime] + 833 [N? Transactions] ?????????????????????????????????? ? 3,955?[N??System Failures]

With multiple regression analysis, operational risk managers can perform some cost-benefit analysis. For instance, if they notice that overtime is a main exposure driver, they could quantify the profit of hiring an additional employee. In our case, hiring one additional employee should reduce overtime and hence lessen the amount of monthly operational losses by a maximum of 4,401x160?=?704,160.

- **Logit and Probit**
  The binomial probit and logit models are the simplest qualitative dependent variable estimators. The probit model is an econometric model

where the dependent variable y_i can be only one or zero. The impact of the independent variable x_i is estimated in $P(y_i=1)=F(x_i?b)$ where b is the parameter to be assessed and F the normal cumulative distribution function.

Formula 3

The Normal Cumulative Distribution Function

$$F(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-x^2}{2}\right) dx$$

Quantitative specialists will use the probit model to estimate the likelihood that employees will leave the company or the core system will break down. When the dependent variable might take one of the discrete choices among a finite number of alternatives, quantitative specialists will use the logit model. This model is similar to the probit model except that a different cumulative distribution function is used. To estimate the likelihood of employees working part-time, the logit model might be appropriate.

These techniques allow operational risk managers to run cost-benefit analyses and to quantify some management actions.

V. MANAGEMENT

The whole institution should be concerned with managing operational risk effectively. The main role of the operational risk manager is to produce an overview of the management of the operational risk at each level of the institution. At the same time, it is crucial for the operational risk manager to validate the models of the quantitative specialists.

V.1. Model Validation

In smaller institutions the quantitative specialists frequently validate their own models by the following methods:

- **Back Testing**
  Back testing is the process of verifying whether a model is consistent across time. This can be done by checking the results of running the model with an old sample of data within the model confidence interval, cutting the size of the sample (jackknifing) or increasing its size (bootstrapping).

- **Stress Testing**
  The measure of risk should not rely solely on statistics (when the VaR is exceeded, how large can this loss be?). Stress testing is performing a set of scenario analyses to estimate the effects of extreme events.

In larger institutions the operational risk manager might ask a quantitative specialist from another department to audit the models.

V.2. Internal Controls

Most big losses have been due to internal control weaknesses or lack of compliance with existing internal control procedures. Quality of management and internal controls (segregation of duties, clear management reporting lines and adequate operating and contingency procedures) seem to be the key factors for mitigating operational risk. The operational risk manager has to ensure that key controls are effectively implemented to prevent operational losses or to detect these as soon as possible. The operational risk manager might rely also on

reengineers for this operational auditing.
Reengineering is the rethinking and redesigning of business processes in order to improve performance by reducing costs, increasing speed, avoiding operational errors or ensuring greater accuracy. The Office Support Systems Analysis and Design (OSSAD) (5) method is currently used in the banking industry.

VI. CURRENT STATUS

Operational risk is not at the same stage as market or credit risk. There is no agreed definition, nor is there a standard methodology or systematic regulatory approach.

VI.1. Regulatory Approach

The Basle Committee on Banking Supervision proposed in its June 1999 consultative paper to introduce a capital charge for operational risk. The way this will be done is still unclear. The Committee is soliciting comments on various approaches:

- **Will the Committee adopt a simple standardized approach?**
  A simple standardized approach is easy to implement. But with such an approach some specific institutions might be placed at a disadvantage and could be charged too much.

- **Will it allow internal models?**
  The internal model should be more accurate than the standardized approach. Regulators will have to define the scope of use and the methods of validation of such models. Risk practitioners would rather use their own model while regulators prefer a standardized approach (6).

- **What will be the relation of the operational risk model to the market and credit risk models?**
  The approaches to measure market and credit risk are quite different. For instance, the holding period for a market risk model is ten days, whereas, in the case of credit risk, risk practitioners recommend one year. Ideally, the operational risk model should link market and credit risk models in order to build a firm-wide integrated risk model. However, there is still a long way to go until the risk practitioners develop a firm-wide integrated risk model that combines the three risks in one meaningful measure.

VI.2. Software

To quantify operational risk, most of the ?major? banks are developing their own software. There is, however, some commercial software available (often web-based systems which means they are easy to implement), such as:

- RiskOps from NetRisk
- PaceMaker from PaceMetrics
- ORCA from Operational Risk Incorporated
- Operational Risk from Algorithmics.

With respect to data, NetRisk and the Global Association of Risk Professionals (GARP) have launched an initiative to share operational risk data - the Multinational Operational Risk Exchange.

VII. Concluding Remarks

Operational risk managers want to ensure that the next hit their institution takes will not resemble the one it took before. So it is crucial for them to analyse the occurrence, nature and causes of every operational loss and make their conclusions available to the top management.
The low impact high frequency operational losses are currently well analysed and documented. The trend is to store all the relevant information regarding these losses in a data warehouse. Management information system (MIS) reports then show what are the exposure drivers and what influences they exert on the income statement. Thus, the new data base technology and the quantitative methods applicable make the process of decision-making easier for the top management.
On the other hand, high impact low frequency operational losses are so rare that their quantification is hardly possible, indeed useless. In order to reduce the occurrence of such risks, the operational risk manager must focus mainly on the qualitative aspects. Most of the big consulting firms are providing methods or tools, which include the ?best practice? processes. These methods generally begin by asking each manager for a self-assessment of his or her department exposure to operational risk and thus make every employee risk conscious.

NOTES

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