

Scorecard Models for Operational Risk Management

Modelli di Scorecard per la Gestione dei Rischi Operativi

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Riassunto: L'obiettivo del lavoro è duplice. Viene illustrato il contesto applicativo inerente la misurazione dei rischi operativi, in particolare nell'ambito finanziario, e le principali metodologie statistiche sinora utilizzate a tale scopo. Viene inoltre presentata, sia pure sinteticamente, una proposta metodologica che coniuga rigore scientifico e semplicità interpretativa.

Keywords: Actuarial models, Risk measurement, Scorecard models.

1. Background

The motivation of this paper is to develop efficient statistical methods aimed at measuring the performance of business controls, through the development of appropriate operational risk indicators.

1.1 Institutional context

A number of recent legislations and market practices are motivating such developments. For instance, the “New Basel Capital Accord” (BCBS, 2001), published by Basel Committee on Banking supervision, requires financial institutions to measure operational risks, defined as “the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events”.

In the context of information systems, the recently developed ISO7799 establishes the need of risk controls aimed at preserving the security of information systems. Finally, the publicly available specification PAS56, in setting criteria that should be met to maintain business continuity of IT-intensive companies, also calls for the development of statistical indicators aimed at monitoring the quality of business controls in place.

In this paper we shall focus on the Basel Accord, however keeping in mind that what developed here for the banking sector can be extended to the general enterprise risk management framework (on this matter see e.g. Bonafede and Giudici, 2007).

The Bank of International Settlements (BIS) is the world's oldest financial institution, whose main purpose is to encourage and facilitate cooperation among central banks (for more details see BCBS, 2001).

In particular, BIS established a commission, the Basel Committee on Banking Supervision (BCBS, in order to formulate broad supervisory standards, guidelines and recommend statements of best practice. The ultimate purpose of the Committee is the prescription of capital adequacy standards for all internationally active banks.

In 1988 the BCBS issued one of the most significant international regulations impacting on the financial decision of banks: the Basel Accord. Subsequently, the BCBS worked on a revision, called the New Accord on Capital Adequacy, or Basel II (BCBS, 2001).

1.2 The New Accord on Capital Adequacy

This new framework, developed by the Committee in 2002 to ensure the stability and soundness of financial systems, was based on three 'pillars': minimum capital requirements, supervisory review and market discipline.

The crucial novelty of the new agreement was the identification of operational risk as a new category separated from the others. In fact, it was only with the new agreement that the Risk Management Group of the Basel Committee proposed the current definition of Operational Risk:

“Operational Risk is the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events”.

The risk management group also provided a standardized classification of operational losses into eight Business Lines (BL) and seven Event Types (ET).

The aim of operational risk measurement (for a review see e.g. Alexander, 2003; King, 2001 or Cruz, 2002) is twofold:

- on one hand, there is a prudential aspect, which involves setting aside an amount of capital that can cover unexpected losses. This is typically achieved estimating a loss distribution deriving functions of interest from it (such as the Value at Risk: VaR);
- on the other hand, there is a managerial aspects, for which the issue is to rank operational risks in an appropriate way, say from high priority to low priority, so to individuate appropriate management actions directed at improving preventive controls on such risks.

In general, the measurement of operational risks leads to the measurement of the efficacy of controls in place at a specific organisation: the higher the operational risks, the worse such controls.

The complexity of operational risks and the newness of the problem have driven international institutions, such as the Basel Committee, to define conditions that sound statistical methodologies should satisfy to build and measure operational risk indicators.

2. Actuarial Methods

Statistical models for Operational Risk are grouped into two main categories: 'top-down' and 'bottom-up' methods.

1.1 ‘Top-down’ methods

In the former, risk estimation is based on macro data without identifying the individual events or the causes of losses. Therefore, operational risks are measured and covered at a central level, so local business units are not involved in the measurement and allocation process. 'Top-down' methods include the Basic Indicator Approach (see, for example, Yasuda, 2003 or Pezier, 2002) and the Standardized Approach (see Cornalba and Giudici, 2004 or Pezier, 2002 for more details), where risk is computed as a certain percentage of the variation of some variable, as, for example, gross income, considered as a proxy for firm performance. This approach is suitable for small banks, that prefer a cheap methodology, easy to implement.

1.2 ‘Bottom-up’ methods

'Bottom-up' techniques, instead, use individual events to determine the source and amount of operational risk. Operational losses can be divided into levels corresponding to business lines and event types and the risks are measured at each level and then aggregated. These techniques are particularly appropriate for large sized banks and

those operating at the international level, since they can afford the implementation of sophisticated methods, sensitive to the bank's risk profile. Methods belonging to this class are grouped into the Advanced Measurement Approaches (AMA) (BCBS, 2001). Under the AMA, the regulatory capital requirement will equal the risk measure generated by the bank's internal operational risk measurement system using the quantitative and qualitative criteria set by the Committee. It is an advanced approach as it allows banks to use external and internal loss data as well as internal expertise (Giudici and Bilotta, 2004).

1.3 Statistical approaches

Statistical methods for operational risk management in the bottom-up context have been developed in very recent years. One main approaches has emerged: the actuarial approach.

This method is applicable in the presence of actual loss data, and is based on the analysis of all available and relevant loss data with the aim to estimate the probability distribution of the losses. The most employed methods described, for example, in King, 2001; Cruz, 2002; Frachot et al., 2001; Dalla Valle et al., 2007, often based on extreme value distributions.

Another line of research suggests the use of Bayesian models (see e.g. Yasuda, 2003, Cornalba and Giudici, 2004 and Fanoni, Giudici and Muratori, 2005).

The main disadvantage of actuarial methods is that they rely their estimates only on past data, thus reflecting a backward-looking perspective. Furthermore, it is often the case, especially for smaller organisations, that, for some business units, there are no loss data at all. Regulators thus recommend to develop models that can take into account different data streams, not only internal loss data (see e.g. BCBS, 2001). These streams may be: self assessment opinions, usually forward looking; external loss databases, usually gathered through consortiums of companies; data on key performance indicators.

In the actuarial model, loss events are assumed independent and, for each of them, it is assumed that the total loss in a given period (e.g. one year) is obtained as the sum of a random number (N) of impacts (X_i). In other words, for the j -th event the loss is equal to:

$$L_j = \sum_{i=1}^{N_j} X_{ij}$$

Usually the distribution of each j -specific loss is obtained from the specification of the distribution of the frequency N and the mean loss or *severity* S . The convolution of the two distributions leads to the distribution of L (typically through a Monte Carlo estimation step), from which a functional of interest, such as the 99,9% percentile (the value at risk) can be derived.

Scorecard models

1.1 Self Assessment

The scorecard approach is based on the so-called *Self Assessment*, which is based on the experience and the opinions of a number of internal “experts” of the company, who usually correspond to a particular business unit. An internal procedure of control self

assessment can be periodically done through questionnaires, submitted to risk managers (experts), which gives information such as the quality of internal and external control system of the organisation on the basis of their own experience in a given period. In a more sophisticated version, experts can also assess the frequency and mean severity of the losses for such operational risks (usually in a qualitative way).

1.2 Representation of Self Assessment opinions

Self assessment opinions can be summarised and modelled so to attain a ranking of the different risks, and a priority list of intervention in terms of improvement of the related controls.

In order to derive a summary measure of operational risk, perceived losses contained in the self-assessment questionnaire can be represented graphically (e.g. through a histogram representation) and lead to an empirical non parametrical distribution. Such a distribution can be employed to derive a functional of interest, such as the 99,9% percentile (the value at risk).

Scorecard models are rather useful to prioritise interventions on the control system, so to effectively reduce the impact of risks, ex ante and not a posteriori, as can be done by allocating capital (corresponding to the VaR).

We have built a methodology aimed at summarising concisely and effectively the results of a self-assessment questionnaire. We cannot present the details of the methodology, but a brief sketch of it, in the context of a real application, that we hope can help the reader to understand.

Suppose that we are given 80 events at risk (this is the order of magnitude employed in typical banking operational risk management analysis). They can be traced to the four main causes of operational risk: People, Processes, Systems and External events.

First of all a selected sample of banking professionals (both from the headquarters and the local branches) is obtained. The aims of the questionnaire project have been described in a group presentation. The nature and the structure of each risk question have been devised in a focus group discussion with the top manager of the bank.

The result of this preliminary analysis is that each of the selected professional is asked, for a total of about 80 risk events, his/her opinion on the: frequency, severity and effectiveness of the controls in place for each event.

The number of possible frequency classes is equal to four: daily, weekly, monthly, yearly.

The number of severity classes depend on the size of the capital of the bank, with an average of 6/7 classes, going from “an irrelevant loss” to “a catastrophic loss”.

Finally the number of possible classes of the controls are three: not effective, to be adjusted, effective.

Once interviews are collected, the aim is to assign a “rating” to each risk event, based on the distribution of the opinions on the frequency, controls and severity. Our proposal is to employ the median class as a location measure of each distribution, and the normalised Gini index as an indicator of the “consensus” on such location measure. This results in three rating measures for each event, expressed using the conventional risk letters: A for low risk, B for medium risk, C for higher risk and so on. While the median is used to assign a “single letter” measure, the Gini index is used to double or triple the letter, depending on the value of the index. For example: if the median of the frequency distribution of a certain risk type (e.g. theft and robbery) is “yearly”, corresponding to the lowest risk category, a letter A is assigned. Then, if all interviewed agree on that evaluation (e.g. the Gini index is equal to zero), A is converted to AAA; if

instead the Gini index corresponds to maximum heterogeneity A remains A. Intermediate cases will receive a double rating of AA.

The same approach can be followed for the severity as well as for the controls, leading to a complete scorecard that can be used for intervention purposes.

For visualisation purposes, colors are associated to letters, using a “traffic-light” convention: green corresponds to A; yellow to B; red to C and so on.

Figure 1 presents the results from our scorecard model, for a collection of risk events belonging to People (Internal Frauds) and External Events (External frauds and losses at material activities)

Figure 1. Example of results from our proposed scorecard model.

			CONTROLS	FREQUENCY	SEVERITY
PEOPLE	Internal fraud	1.1.1 Transactions not reported (intentional)			
		1.1.2 Trans type unauthorised (w/ monetary loss)			
		1.2.1 Fraud/credit fraud/worthless deposits			
		1.2.2 Theft/extortion/embezzlement/robbery			
		1.2.3 Malicious destruction of assets			
		1.2.4 Forgery			
		1.2.5 Check kiting or smuggling			
		1.2.6 Account take-over/impersonation/etc.			
		1.2.7 Tax non-compliance/evasion (wilful)			
		1.2.8 Bribes/kickbacks			
		1.2.9 Insider trading (not on firm's account)			
		1.2.10 Theft of information (w/ monetary loss)			
EXTERNAL	External fraud	2.1.2 Hacking damage			
		2.2.1 Theft/Robbery			
		2.2.2 Forgery			
		2.2.3 Check kiting			
		2.2.4 Clonation of credit cards, p.o.s., atm			
	Danni ad attività materiali	5.1.1 Natural disaster losses			
		5.1.2 Losses from external sources (terrorism, vandalism)			

From Figure 1 it turns out that the event 1.2.6 should be given a priority 1 of intervention, as controls are not effective, and both frequency and severity are yellow. Other events at risk include 2.2.1 and 2.2.4 which have a high frequency and medium quality controls. We remark that the opinion on the severity is usually considered second in priority determination as it typically concerns a mean value which cannot be modified by the action of controls.

3. Integrated scorecard models

While scorecard methods typically use self-assessment data, actuarial models do use internal loss data.

The disadvantage of these approaches is that they consider only one part of the statistical information available to estimate operational risks. Actuarial methods rely only on past loss data (backward looking) and, therefore, do not consider important information on the perspective and the evolution of the considered company; on the other hand, scorecard methods are based only on perceived data (forward looking) and, therefore, do not reflect well past experiences.

A further problem is that, especially for rare events, a third data stream may be considered: external loss data. This source of data is made up of pooled records of losses, typically higher than a certain value (e.g. 5000 €), collected by an appropriate association of banks.

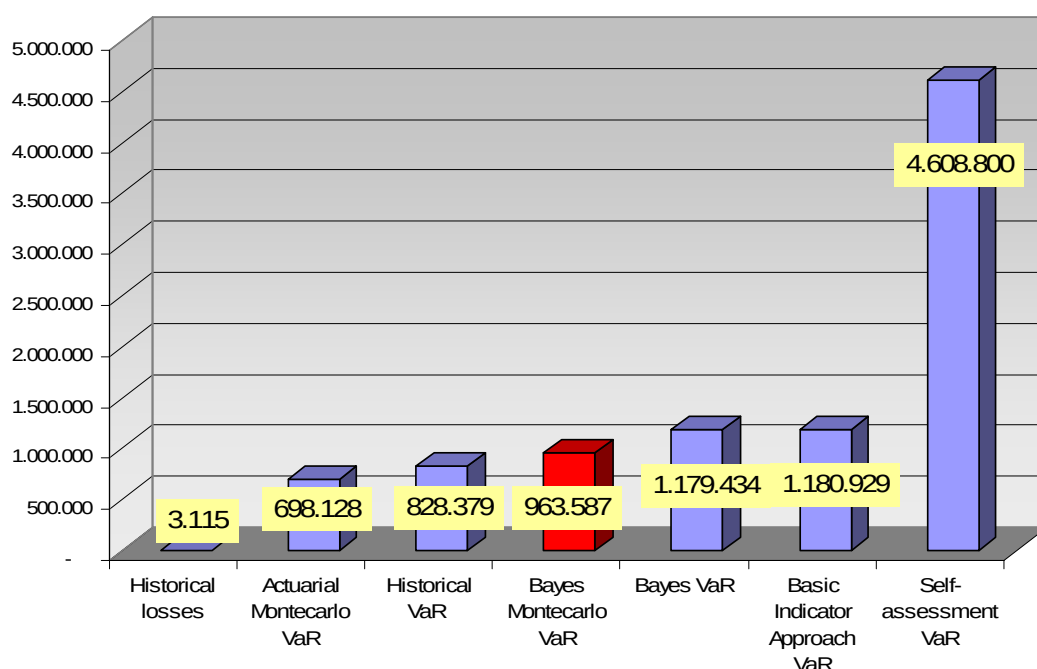
It becomes thus necessary to develop a statistical methodology that is able to merge three different data streams in an appropriate way, yet maintaining simplicity of interpretation and predictive power. Here we shall propose a flexible nonparametric approach that can reach this objective. Such an approach can be justified within a non parametric Bayesian context.

Our approach considers, for each event, all loss data occurred in the past as well as the expected self assessment losses for the next period. The latter is counted as one data point, typically higher than actual losses, even when is calculated as a mean loss rather than as a worst case loss.

Putting together the self-assessment data point with the actual loss data points we obtain an integrated loss distribution, from which a VaR can directly be calculated. Alternatively, in order to take the losses of the distributions more correctly into account, a Monte Carlo simulation can be based on the given losses, leading to a (typically higher) Monte Carlo VaR, parallel to what is usually done in the actuarial approach.

In Figure 2 we compare, for a real database, the Value at Risk obtained under a “pure” self-assessment approach, with the actuarial VaRs (both historical and Monte Carlo based) and the Integrated (Bayesian) VaR (both simple and Monte Carlo). For reasons of predictive accuracy, we build all methods on a series of data points updated at the end of the year 2005; calculate the VaR for the year 2006 (possibly integrating it with the self-assessment available opinions for 2006) and compare the VaR with the actual losses for 2006. We also calculate the VaR that would be obtained under the simple Basic indicator approach (BIA), suggested by Basel II to the small and medium-sized bank. The BIA approach amounts to calculating a flat percentage (15%) of a relevant indicator (such as the gross income), without statistical elaborations.

Figure 2: Example of results from our integrated scorecard model.



From Figure 2 it turns out that both our proposed models (Bayes Var and Bayes Monte Carlo) lead to an allocation of capital (represented by the VaR) lower than the BIA approach, and higher than the observed losses. Although these results are achieved by the actuarial models as well (Historical and Actuarial Monte Carlo) we believe that a prudential approach, as expressed by our proposal, is a more sound approach, especially in a longer time horizon.

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References

- Alexander, C. (2003) Operational Risk: Regulation, Analysis and Management, *London. Financial Times, Prentice Hall*.
- Basel Committee on Banking Supervision (2001) Working Paper on the Regulatory Treatment of Operational Risk, (www.bis.org).
- Bonafede, E.C. and Giudici, P. (2007) Bayesian networks for enterprise risk assessment. To appear in *Physica A*.
- Cornalba, C. and Giudici, P. (2004) Statistical models for operational risk management. *Physica A*, 338, 166-172.
- Cruz M. (2002) Modeling, Measuring and Hedging Operational Risk, *John Wiley & Sons, Chichester*.
- Dalla Valle, L., Fantazzini, D. and Giudici, P. (2007) Copulae and Operational Risk. To appear in *International Journal of Risk Assessment and Management*.
- Fanoni, F., Giudici, P. and Muratori, M. (2005). Il rischio operativo: misurazione, monitoraggio, mitigazione. *Il Sole 24 Ore*.
- Frachot, A., Georges, P. and Roncalli, T. (2001) Loss distribution approach for operational risk. *Working Paper, Groupe de Recherche Opérationnelle du Crédit Lyonnais*.
- Giudici, P. and Bilotta, A. (2004) Modelling Operational Losses: a Bayesian Approach, *Quality and Reliability Engineering International*, 20, 407-417.
- Giudici P. (2003) Applied Data Mining: Statistical Methods for Business and Industry. *John Wiley & Sons, Chichester*.
- King J. (2001) Operational Risk. Measurement and Modelling, *John Wiley & Sons, Chichester*.
- Pezier, J. (2002) A constructive review of the Basel proposals on operational risk. *ISMA Technical report, University of Reading*.
- Yasuda, Y. (2003) Application of Bayesian Inference to Operational Risk Management. *Technical report, University of Tsukuba*.