Risk books

Operational Risk Capital Models

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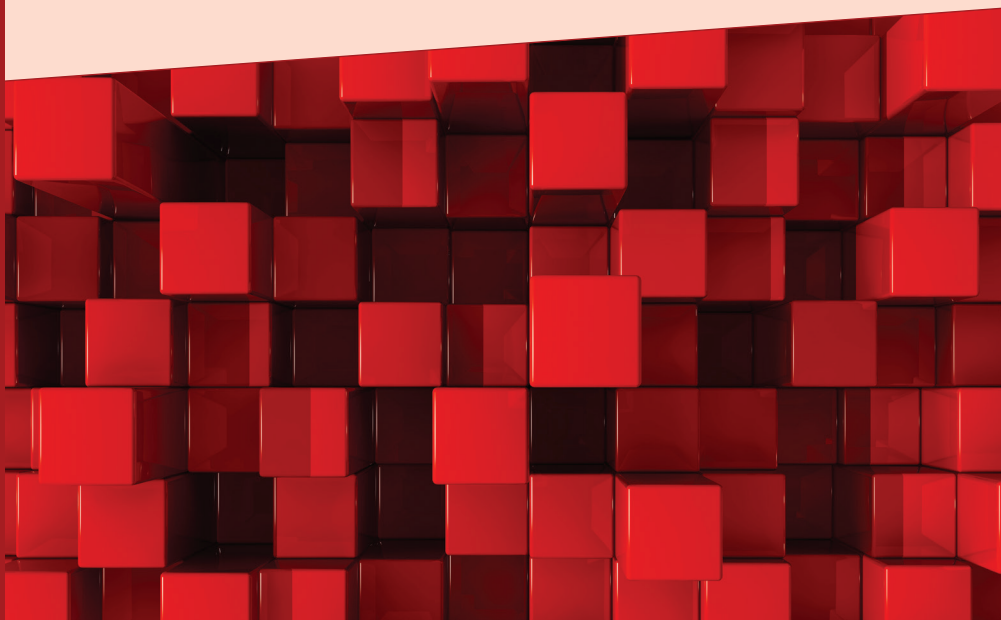

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Foreword

These are interesting times for operational risk. Since the beginning of this century when it became a more established risk discipline blessed by the Basel II accord, operational risk has had a lesser status than market and credit risk. These financial risks would be more visible to the board and executive management; and, if business units want any change in the risk profile, such as a value-at-risk limit increase, these business requests would have to be vetted by market and credit risk managers.

Operational risk managers would not have the same interaction, mostly because the models used by risk managers were not designed with sensitive analysis tools that would allow analysts to understand the impact of new deals or transactions in the overall capital requirement. Most recently, financial institutions have been subject to very large losses that originated from bad conduct during the financial crisis or even after that period. These large losses are obviously made to the bank's operational loss databases and create a significant challenge for modellers.

Considering that operational risk severity distributions are already heavy-tailed, the inclusion of these extremely large settlements caused a spike and also brought volatility to the regulatory capital for these firms. These losses were so important that they impacted on the results of these large financial institutions, turning operational profits into losses on their quarter and annual earnings results. These settlements helped to call the attention of the board of directors and executive management to the importance of having a robust operational risk management within their organisations.

Currently, operational risk is seen as a key risk in financial institutions and operational risk managers are beginning to get invited to opine in key decisions and large strategic deals. However, the modelling challenge persists, and this is where *Operational Risk Capital Modelling: Compliance and Integration into Management* comes with a significant contribution to close this gap.

The book covers in detail all the building blocks of operational risk modelling with a very pragmatic, step-by-step view from industry practitioners, so the reader can see how the operational risk capital is actually calculated and stress-tested. The authors move from the technicalities of capital calculation to the integration of this capital into the strategic and tactical decisions of the financial institution. In my view, this book is a strong contribution to operational risk management in this new era.

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About the Editors

Brenda Boultwood is the senior vice president of Industry Solutions at MetricStream. Previously, she served as senior vice president and chief risk officer at Constellation Energy, before which she served as global head of strategy for alternative investment services at JP Morgan Chase. At Bank One Corporation, she served as head of corporate market risk management and counterparty credit and head of corporate operational risk management, before advancing to head, global risk management for the company's Global Treasury Services group.

Boultwood has also worked with PricewaterhouseCoopers (PwC) and Chemical Bank Corporation. In addition, she has spent time teaching at the University of Maryland's MBA programme. She was a member of the CFTC Technology Advisory Committee, and has also served on the Board of the Global Association of Risk Professionals (GARP). She currently serves on the board of the Committee of Chief Risk Officers (CCRO).

Boultwood graduated with honours from the University of South Carolina with a bachelor's degree in international relations. She also earned a PhD in economics from the City University of New York.

Rafael Cavestany has over 15 years of experience in the financial services industry covering the banking and insurance sectors. He currently works as a director in True North Partners Group and SKITES. Before, Cavestany worked at Everis as executive director of the risk management practice and at PwC as senior manager.

He has worked on projects for a number of leading financial institutions in the USA, Canada, the UK, Spain, Italy, Latin America and South Africa, and his experience is focused on consulting projects for the development of risk management analytics software solutions and the corresponding methodologies, workflows and data requirements with special emphasis on economic capital and operational risk modelling. Regarding operational risk modelling, he has under-

taken projects in the insurance, banking, energy, oil and gas, and food industries and led the development of the software solution used in the examples of this book, OpCapital Analytics.

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Moguerza's professional expertise is focused on computational and applied mathematics, optimisation, Six Sigma quality, data mining, pattern recognition methods and energy risk management. He has publications in highly ranked scientific journals.

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Introduction

Rafael Cavestany

We write this book (2015) while the world economy is still recovering from the largest economic crisis since the Great Depression. Many of the current crisis causes can be traced to consecutive operational failures (Robertson 2011), including mortgage fraud, model errors, negligent underwriting standards and failed due diligence combined with loosely implemented innovation trends in finance. Mortgage originators, mortgage bundlers, credit-rating agencies, asset managers, investors and, ultimately, regulatory agencies were responsible for many of these operational failures.

The consequences have included severe depletion of capital and undermined confidence in the financial system, causing the downfall of many large, well-established financial institutions, and forcing a deep restructuring of the financial sector in many of the most advanced economies.

The Basel II Committee defines operational risk as "the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events". Internal processes, people, and systems or external events directly impact on the institution's business and strategy execution, endangering the institution's survival, if operational risk is not managed adequately. In fact, even individual operational risk events have caused the collapse of historical institutions (instance Baring PLC in 1995) or produced great damage into their capital base (Société Générale in 2008 and UBS in 2011) in addition to undermining the confidence in these institutions' capacity for managing risks.

These past events remind us how vulnerable our organisations are to new threats and that institutions should thoroughly identify

emerging menaces. For instance, innovation trends in banking, such as smartphones, tablets and self-service technologies, are energetically exploding, while the sophistication of cyber-attackers seems to increase, too frequently, faster than the institutions' capacity to respond effectively. On top of this, the upsurge of social networks dramatically increases the reputational impact and the development speed of some operational risk events.

Hence, operational risk should be pervasively analysed, quantified and managed for an adequate understanding of its potential economic and operative consequences, identification of causes and introduction of effective remedies. For this purpose, a granular operational risk capital modelling is a critical tool that allows institutions a deep understanding of the operational risk profile and permits enterprise-wide operational risk management.

In spite of the highly disruptive impact and unexpected nature of operational risk events, operational risk capital modelling is far too often considered less critical than the modelling of credit and market risk capital. Many institutions have successfully integrated credit and market risk quantification into management, in critical processes such as asset approvals, pricing, risk appetite, risk limits and performance measurement. On the other hand, operational risk quantification remains all too frequently dedicated principally to the calculation of a regulatory capital figure and has little integration into the daily mitigation of operational risk.

This is due, in part, to the more evident link of credit and market risk capital with specific assets in the balance sheet and their risk characteristics (probability of default, price volatility and others), enabling a risk management differentiated by asset. On the contrary, in operational risk, capital is calculated at organisational-entity level (business unit (BU), business area, department or other), sometimes being more challenging in its calculation down to a very granular level. Additional reasons include the absence, until now, of sufficiently robust models to determine an accurate operational risk profile, together with the impact of mitigation actions in such a risk profile; and the underimplemented methods and procedures for the integration of the operational risk capital results into the day-to-day risk management of the institution and strategic and business planning.

However, the implementation of a robust operational risk capital

model[1] framework, in a financial institution, including its solid integration into the institution management, can provide the organisation with great benefits, far beyond the regulatory compliance with Basel II/III or Solvency II, or the capital cost savings with respect to the standardised or basic indicator approaches.

The inputs used in capital modelling – internal loss data (ILD), external data (ED), scenario analysis (SA) and business environment and internal control factors (BEICFs) – deliver us an insightful view of the operational risk profile faced by the institution: the collection and modelling of ILD allows an understanding of the likely losses segmented by risk type and organisational entity, and their projection to unlikely but possible events. SA offers information on rare but highly disruptive events for the financial institution that are not captured in the internal-loss-data set. Scenarios can be complemented with ED, which provides the experience of other institutions into the analysis, complementing the view of the potential risks being faced by the institution. BEICFs provide us with an updated operational risk profile and its future possible evolution, thanks to the use of key risk indicators (KRIs), risk and control self-assessment (RCSA) and internal audit scores. These inputs to the capital model can be used to identify areas requiring mitigation action plans and can be embedded into other risk management processes.

Also, the studies required in determining SA, risk dependencies, stress testing and distribution tails provide a unique opportunity for different risk owners to meet in order to analyse and discuss the risks faced in their departments, increasing risk awareness and identifying the most effective mitigation. The construction of predictive analytics on BEICFs can help in identifying loss drivers and create early warnings about changes in risk profile and so on, while being used for creating a more foreseeing estimation of capital.

Finally, the capital figures estimated by the model can be embedded in the strategic and operational business planning process for more accurate financial planning, resource allocation, performance measurement and management of the risk profile. The capital model outputs can be used in the institution's risk appetite framework, helping to enforce the risk management mandate by the board of directors of the institution and a more efficient control of the financial resources of the organisation. All this will facilitate a better implementation of the institution strategy. Then, the capital

model helps to determine the economic business case for the implementation of mitigation plans, providing a risk–reward perspective on risk mitigation.

All in all, an advanced operational risk capital model allows for a more reliable operational environment and significant cost savings from fewer loss events, prevention of high-severity events, capital costs and precision in financial planning. This represents an important win for the institution, given the disruptive and unexpected nature of operational risk events.

Indeed, it is hard to imagine that means other than an advanced operational risk capital model would be able to provide such benefits. It is worth noting that an advanced operational risk capital model probably provides risk mitigation information at least as useful as those more commonly implemented capital models of credit and market risks, such as Moody's KMV and RiskMetrics.

In this context, methodologies for operational risk quantification are less consolidated than those of market and credit risks, and calculation standards are yet to be widely accepted.

Some of the reasons for the absence of widely accepted calculation standards are the significant challenges involved in performing robust operational risk modelling and its integration into the daily management of the institution. The robust calculation of operational risk depends on a strong modelling methodology and a thorough collection of institution-specific high-quality operational risk data from multiple processes and organisational units. Also, the integration of capital calculation into the institution's daily management depends on the development of information and analytical processes, allowing the link between operational risk calculations and risk mitigation measures such as action plans, insurance, and process improvements. Finally, all of the above is highly dependent on the support of automated processes and the provision of an adequate governance over those processes.

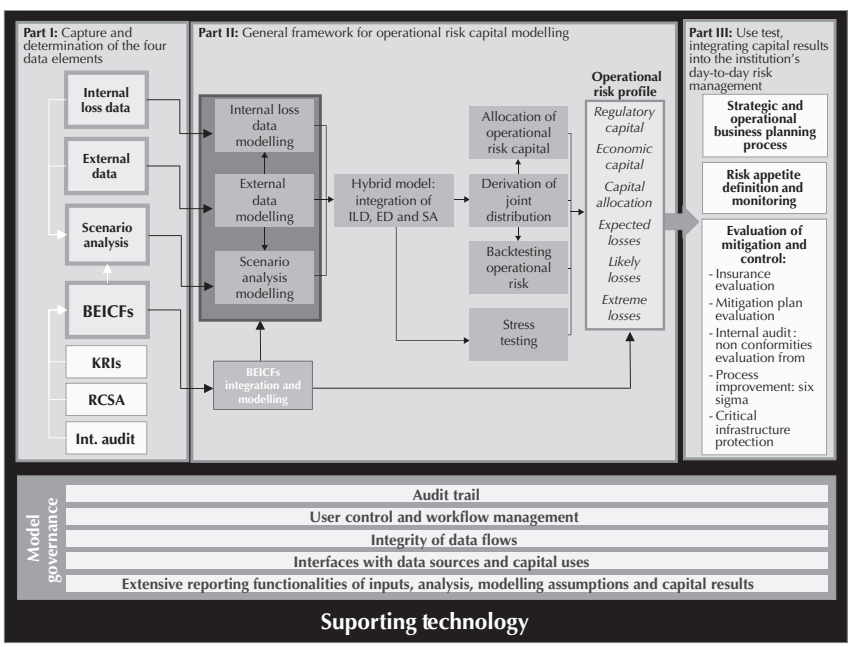
More specifically, the modelling challenges in operational risk quantification include: data quality; difficulty of modelling extreme events; need for a forward-looking capital estimates; the qualitative nature of SA; the need for stable operational risk capital estimates; the selection of modelling assumptions; the diversity of nature and origin of operational losses; the integration of different data elements; the availability of a technology that adequately supports

all analytical processes, data integrity and governance functions; and the requirement of a regulatory validation.

Overcoming these challenges requires a deep analysis and the collection of valuable operational risk information on exposures, dependences and potential events. The modelling of operational risk capital in fact requires a deep understanding of these. Moreover, if these are linked to risk mitigation, the institution obtains one of the greatest benefits, if not the greatest benefit, of the advanced operational risk capital modelling approach.

This book contains the experience of its authors during the successful implementation in organisations of operational risk capital models, best practices and industry standards, and the integration of the capital results into day-to-day risk management. We use the challenges described above to define the required elements in the operational risk capital modelling framework. Figure 1.1 shows all the interconnected elements involved in the process of achieving a robust estimation of operational risk capital that correspond to the chapters in the book.

Figure 1.1 High-level workflow for robust operational risk capital modelling framework



This framework is structured in three parts which correspond to the chapters and parts of this book.

Part I, "Capture and Determination of the Four Data Elements", defines the foundation of an operational risk modelling framework, since the capital model outputs' quality cannot exceed that of its inputs. Within Part I, we present two chapters:

- "Collection of Operational Loss Data: ILD and ED". This chapter presents a common understanding of what is operational risk loss and what are the key considerations when collecting operational risk internal losses and using external data.
- "Scenario Analysis Framework and BEICFs Integration". Here, we present the key elements for scenario analysis collection, including all supporting information (including BEICFs), actions for bias mitigation, scenario rating and scenario validation methods.

Part II, "General Framework for Operational Risk Capital Modelling", includes a thorough description of the end-to-end process to quantify the operational risk profile of the institution, including the modelling of each of the data elements, creating a hybrid model, estimating operational risk correlations, generating the join distribution, allocating capital, and more. This part has the following chapters:

- "Loss Data Modelling: ILD and ED". This chapter presents the process for modelling loss data, starting with exploratory data analysis (EDA), defining the appropriate modelling granularity, defining an optimal threshold, determining the tail weight, fitting distributions and goodness of fit (GoF) analysis under different methods, analysing stability of capital estimates, evaluating the realism of the models created and external data scaling.
- The chapter titled "Scenario Analysis Modelling" describes how to translate the results of scenario analysis into distributions in a scenario-based approach (SBA). It provides methods for controlling the tail shape during the fit and splitting scenarios into lower organisational entities.
- "BEICFs Modelling and Integration into the Capital Model"

presents methods of integrating BEICFs into a capital model, including a score-card method, its modelling or its use to estimate operational risk correlations based on expert judgement.

- The chapter titled "Hybrid Model Construction: Integration of ILD, ED and SA" introduces different methods for creating a hybrid model using different data elements, including implementation of credibility theory for determining the weight that each data element should have in the hybrid model.
- "Derivation of the Joint Distribution and Capital Allocation" introduces the methods for creating a joint distribution from which to derive the operational risk profile for the use test. This includes the Monte Carlo simulation, operational risk correlations, copulas for the aggregation of the different operational risk categories (ORCs), capitalisation of operational risk and allocation of the operational risk capital.
- Next, "Backtesting, Stress Testing and Sensitivity Analysis introduces different methods to backtest and stress test the operational risk model.
- "Evolving from a Plain Vanilla to a State-of-the-Art Model" concludes Part II. Here we present the typical path describing the evolution from a plain vanilla model to a highly developed model fully integrated in the day-to-day management of the institution.

In Part III, "Use Test, Integrating Capital Results into the Institution's Day-To-Day Risk Management", management and information processes are implemented to integrate the operational risk profile into the daily risk management of the institution. Part III is divided into two chapters:

- "Strategic and Operational Business Planning and Monitoring" presents the key consideration when integrating the risk profile from the capital model into the business planning process, and its monitoring of the implementation of the plan using an operational risk appetite framework.
- In "Risk–Reward Evaluation of the Mitigation and Control Effectiveness" we introduce several detailed examples of how to embed the operational risk capital results into daily risk management together with the risk/reward evaluation of the impact of

mitigation actions, into the risk profile, and the determination of an optimal mitigation portfolio using Adversarial Risk Analysis.

All the above informational and analytical processes should have a governance framework that includes audit trail, user control, extensive reporting, workflow management for the validation of modelling assumptions, etc. Finally, the technology around this framework limits modelling error possibilities and facilitates a solid and timely execution of all the modelling, documentation and governance.

The purpose of this book is to present to the practitioner the methods and processes required to address all the above challenges and to help in making the practical decisions for determining the most adequate model for projecting the institution operational risk capital needs. In the different sections, ample references are provided to support the different methodologies proposed.

Additionally, since in practical terms, the main challenge is the fact that operational risk capital models in financial institutions need a regulatory approval, we refer these methods to the guidelines issued by the Basel Committee on Banking Supervision named "Operational Risk – Supervisory Guidelines for Advanced Measurement Approaches" (BCSG-AMA). We use this reference because it is the most comprehensive international document for operational risk capital supervisory purposes. The other major regulatory initiative, Solvency II, is initially a European Union legislative measure, although it is likely to be adopted by many other jurisdictions once it is finally approved and implemented in the European Union. Nevertheless, the methods proposed are valid for any regulation. After all, regulators and supervisors share concerns when seeking to guide institutions in their implementation of solidly supported capital models, which can be externally validated for their use in guaranteeing solvency.

Therefore, the methodologies described in the book can be directly applied to Solvency II operational risk capital internal models also. In fact, we have developed some of these methods working for companies that seek to be Solvency II-approved.

We provide now a more extensive explanation of each of the modelling challenges and, later, Parts I, II and III present the mathematical and methodological processes that may be used to deal with these modelling challenges.

Although this work is focused on providing answers to the regulatory guidelines of Basel II/III and Solvency II, the methods proposed are perfectly applicable to operational risk modelling in any financial and nonfinancial organisation. In fact, the regulatory guidelines are meant to provide robustness, transparency and governance over a quantitative model, and thus can be used for the same purpose by companies in any industry. The implementation of this type of model in a nonfinancial industry may provide the organisation with even greater benefits than those that would be enjoyed by a financial institution, because operational risk is frequently more significant than other risks.

CHALLENGES OF OPERATIONAL RISK ADVANCED CAPITAL MODELS

The data quality of the capital inputs

Data quality represents the foundation of an operational risk capital model, as the quality of the model output cannot exceed that of its inputs. Data quality affects all the four data elements of the capital model (ILD, ED, SA and BEICFs).

ILD must be collected with completeness (BUs, size, risk types and other considerations), ensuring its consistency with accounting, and each event should contain specific data fields appropriately populated. Additionally, the collection should follow a particular definition and methodologies, permitting the correct modelling of operational risk loss distributions (an example of these definitions and methodologies can be found in the "Operational Risk Reporting Standards" of the Operational Riskdata eXchange Association (ORX)). To guarantee the adherence to these, it is necessary to implement a workflow with the corresponding approvals where the data quality is validated before being ratified for quantification. Finally, the ILD collection ideally should guarantee a trail and have adequate data certificates (see Chapter 2).

To obtain an SA with the adequate quality, several issues should be addressed, such as avoiding biases, participant training, validation processes and consistency analysis with other metrics from the Operational Risk Measurement System (ORMS), see Chapter 3.

BEICFs' incorporation into the capital model is probably the most challenging and will require that elements such as RCSA and KRIs to

have sufficient frequency and completeness for their embeddedness into the capital model (see Chapters 3 and 6).

Perhaps ED is the least problematic of the four data elements regarding data quality. ED is delivered, in most cases, by an external provider who has adequate data quality controls. Frequently, the ED provider is a data consortium where data from several institutions is shared. This permits us to enjoy the data quality of more experienced member institutions, as the consortium requests strong quality standards to all participants. Nevertheless, receiving loss data from consortia most frequently implies sharing the institution's own ILD, which, in turn, should have the appropriate quality and be compliant with consortium standards. Therefore, access to consortium data is eventually subject to the institution's ILD quality. Finally, external data entails other issues such as its representativeness of the institution's risk profile, which are later addressed in Chapters 2 and 4.

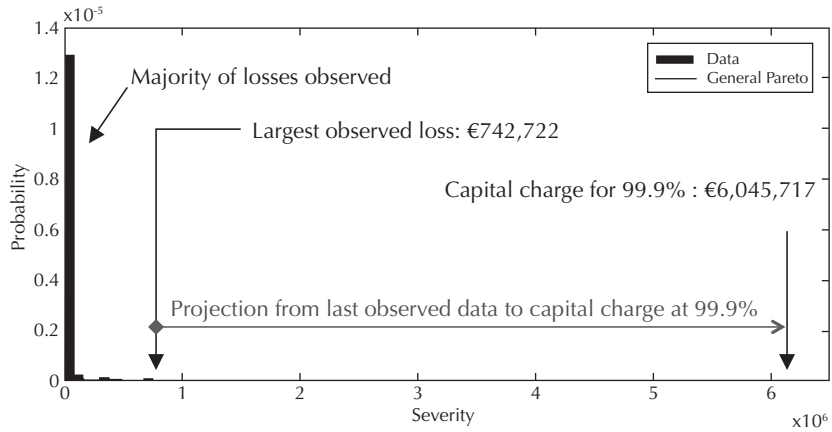
Modelling operational risk extreme events

In any risk type (market, credit, operational and so forth), capital charge is driven by extreme and exceptional events. In fact, under regulatory frameworks (Basel II/III and Solvency II), capital should be sufficient to absorb losses occurring with a higher probability than 0.001 in a year (corresponding to a confidence interval of 99.9%). The use of such a low probability of losses to determine capital implies that exceptional loss events have not necessarily been observed by the institution. This requires the creation of a statistical model to project out from observed loss data.

Determining operational risk capital under Solvency II or Basel II/III's solvency standards is even more challenging, as operational risk distributions generally have strong fat-tail behaviour. Fat-tail behaviour implies that those extreme exceptional events represent a large multiple of what is usually observed. Because traditional modelling is mostly based on observed data, calculating operational risk extreme events requires a challenging projection beyond the observed data.

For the sake of clarity, consider the example in Figure 1.2, which represents the histogram of internal loss data with fat-tail behaviour in a linear scale.[2] The required capital, computed under a 99.9% solvency standard by fitting a generalised Pareto distribution to the loss sample with fat-tail behaviour and using the single-loss-

Figure 1.2 Capital charge in a fat-tail severity distribution



approximation method, demonstrates this point. It can be seen that the capital charge is approximately nine times larger than the higher observed loss. Also, the capital charge is a very large multiple of the average observed loss.

Modelling extreme events can be addressed with extreme value theory (EVT) and fat-tail distributions (see Chapter 4). Nevertheless, fat-tail distributions are highly sensitive to changes in the underlying modelling sample and may deliver unstable capital charges.

The scarcity of observed extreme losses can be tackled by the use of external data and expert judgement as an input to the modelling. In fact, the use of expert judgement in operational risk modelling is required by the supervisory guidelines and it is named SA (see Chapter 3).

Performing a forward-looking capital estimation

Any capital requirement calculation is addressed to absorbing losses occurring in the years ahead. Most commonly, capital requirements are calculated for a time horizon of one to three years. Therefore, these requirements should be calculated with a forward-looking spirit. Forward-looking operational risk capital calculation is challenging, as the institution's control environment continuously evolves, business progresses and the external environment changes.

These evolving circumstances imply that historical operational

risk data is less representative when it originates from several years prior to the modelling date. As time passes, internal controls may have been improved, processes automated, new products or services launched or part of existing offerings may have increased their weight in total activity. Also, the external business environment may affect activity levels, the nature of fraudulent actions or attacks, new technologies implemented by the institution and clients, alternative distribution channels used, and so on. All of this changes the size and frequency of the operational losses of the institution decreasing the historical data relevancy.

Additional issues can be found when institutions initially implement their formal operational risk management programmes. The loss data collection process may take a couple of years to be perfected and achieve a complete coverage within the institution. The implementation of a solid internal loss data collection process from the very start of the operational risk management programme will help to mitigate this issue. Moreover, a formal and systematic operational risk management programme is expected to reduce the size and frequency of operational losses diminishing the relevance of data collected before the implementation of the programme. Thus, the older the loss data, the less relevant it is for determining future capital requirements.

The problem of old data representativeness is present in any science using historical data to predict future events, such as actuarial, engineering, manufacturing, etc. This problem is addressed using several methods including the following: assigning a lower weight to older data during the distribution fit or simulation of total losses see Chapter 4); introduction of additional data elements such as expert judgement in the form of scenario analysis (see Chapter 7); implementation of credibility theory (see Chapter 7) to determine the weight of the different data elements; analysing frequency trends and distribution characteristics' evolution and projecting them accordingly (see Chapter 4).

In fact, the BCSG-AMA requires financial institutions to use BEICFs as one of the four main elements for the modelling (ILD, ED and SA are the other three elements) to reflect the forward-looking character of the operational risk capital. Embedding BEICFs into capital estimation is a challenge given the difficulty in establishing a direct link, through the use of statistical analysis, into the capital

modelling (see Chapter 6). Nevertheless, predictive models relating KRIs, internal audit scores or even RCSA scores can be created for adjusting the expected frequencies of the capital model and other capital metrics (see Chapter 6). This type of analysis is facilitated by the existence of an appropriate database of BEICFs and event data, generally supported by a governance, risk and compliance (GRC) solution.

The qualitative nature of scenario analysis

Scenario analysis is one of the data elements that should be part of an advanced capital model for operational risk. It is a critical component used to complement the modelling of potential extreme losses, which have not been observed by the institution but are possible.

Scenario analysis is based on expert judgement and, therefore, is subject to well-reported human cognitive biases, which pose a significant threat to the quality of the answers obtained. Also, given the qualitative nature of the answers to the scenario analysis, a validation process should be established. Therefore, to maximise the quality of a scenario analysis, the institution should establish a solid process to inform the experts on all available information, provide training for helping experts in structuring their analysis, establish strategies for the mitigation of cognitive biases, articulate adequately scenario questions and, finally, establish a strong process for the validation of expert answers.

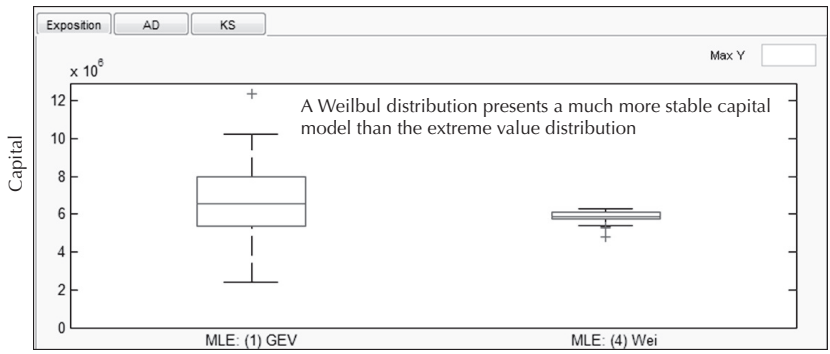
The need for stable capital estimates

Stability of results in operational risk modelling is required because the capital budgeting process needs stable capital estimations in order to programme resource allocation, capital-raising actions, dividend payments, etc. Additionally, the robustness of the operational risk model may be in doubt if capital requirements change significantly every time newly collected loss data is added to the modelling sample.

Unstable capital estimates may have several origins, which include the selection of the model type and the insufficiency of historical data for modelling.

The selection of an inadequate model, for instance, looking simply at the goodness of fit, can have a major impact on capital stability, when the model is very sensitive to changes in the fitting sample. Figure 1.3 illustrates the impact on capital stability estimates by

Figure 1.3 Capital stability challenge



selecting different modelling options. The capital stability calculations have been performed following the resampling method described in Chapter 4. The box plot graph represents the potential capital dispersion given new losses coming from the same loss-generation process. It can be seen how modelling with one distribution provides more stable capital estimates.

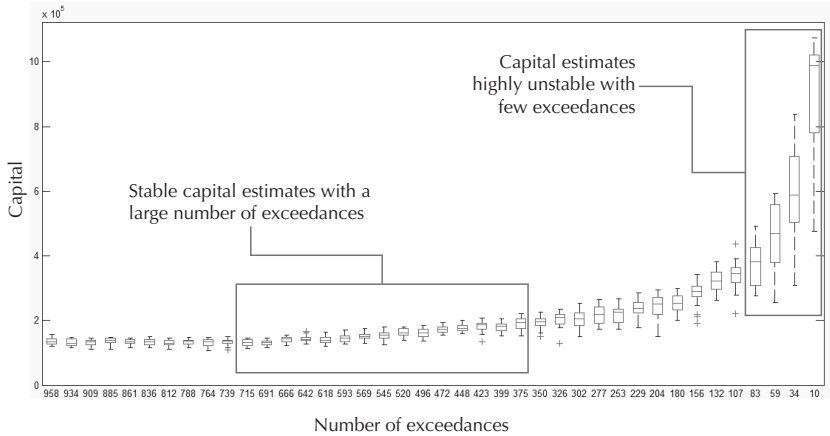
Figure 1.4 illustrates the stability of capital estimates due to insufficiency of historical data for modelling. It represents capital stability as the number of exceedances used in the fitting process (see Chapter 4). It can be seen that capital is more stable the higher the number of exceedances used, and becomes more volatile the fewer the number of exceedances. The reason is that, as the size of the sample decreases, there is more uncertainty on the real loss distribution explaining the behaviour. As an example, in Figure 1.4, the divergence in capital estimates increases as the size of the sample decreases, by increasing the modelling threshold.

Therefore, in operational risk capital modelling, the modeller should implement processes to evaluate the stability of modelling results. Some methods of performing this analysis are described in Chapter 4.

Selection of modelling assumptions

While, for market risks and credit, the distribution modelling standards are restricted to some distribution families (normal, lognormal, binomial and so on), operational risk modelling does not have any restrictions on the distribution family, provided it delivers

Figure 1.4 Capital stability by number of exceedances



an adequate fit. Therefore, a wide variety of distributions are used for modelling operational risk as described in Appendix I.

If *p*-values from tests are solely considered, the modeller may face multiple distribution assumptions to select from and no solid argument to prioritise one over the rest. The modelling process should incorporate extensive analysis to allow a solid modelling assumption selection (see Part II for methods of selecting distributional assumptions, including graphical and numerical goodness-of-tests analysis, stability of capital estimates, goodness-of-fit measures adjusted to the degrees of freedom of the distribution, evaluation method of the realism of the distribution estimates, tail control measures, and others).

Wide variety of sources and risk types of operational losses

Operational losses originate in any process or organisational unit in the institution and may be of very different natures. The source and nature of losses determine the loss frequency and severity distribution, making operational risk losses a highly heterogeneous sample of losses with different frequencies and distributional characteristics.

Figure 1.5 provides examples of operational risks in a financial institution spread over all activities, departments, BUs, etc. A similar representation can be done for insurance, asset management and so forth, or even for nonfinancial sectors such as energy and utilities.

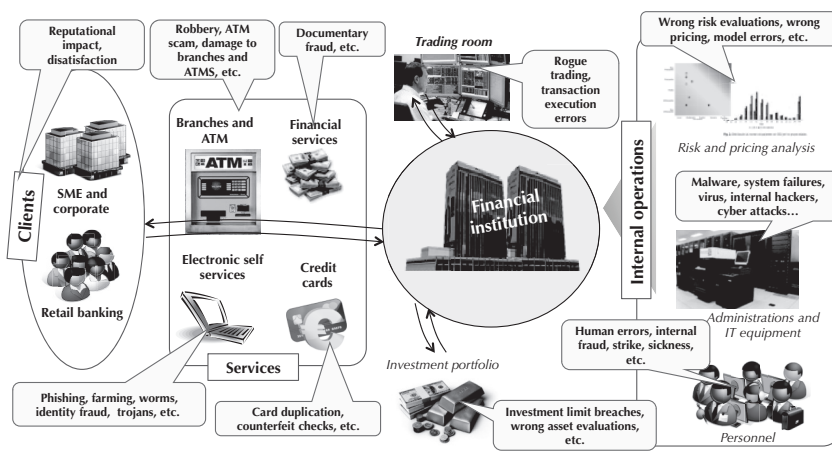
Ideally, these circumstances would be resolved by creating a

specific model for every process and loss type. In practice, this implies segmenting an already limited data sample, thus preventing a robust modelling of highly specific operational risks.

The creation of a larger modelling sample, can be addressed by aggregating losses by risk type Level 1 (after Basel Committee classification and Solvency II guidelines) and BUs. Although sample aggregation creates larger datasets, allowing its modelling, the aggregated data sample becomes a highly heterogeneous amalgamation of losses, resulting in other modelling challenges.

This heterogeneity can be addressed by segmenting the data sample by severity segments, as size is a clear differentiation factor for loss nature (see Chapter 4). Small losses may come from noncritical processes, while large losses may stem from processes impacting on serious aspects of the bank's activity, involving large monetary amounts and stronger controls. Loss severity distribution can be modelled according to multiple segments, to differentiate high-severity tail events from medium-sized and small-sized losses. Lower losses are generally most frequent and can be integrated into the simulation by directly resampling over the historical distribution. Tail losses are generally modelled using fat-tail distributions and body losses using a light-tail distribution.

Figure 1.5 High-level description of the activities in a financial institution



The integration of multiple data elements

Each of the four data elements (ILD, ED, SA and BEICFs) provides an important piece of information for the correct modelling of the complete operational risk distribution, from likely losses to highly unlikely but possible losses. Also, the weight and influence of each of the data elements should be determined using an unbiased method.

This represents a challenge for modelling, as it requires the use of nonstandard statistical and simulation methods to consolidate the different sources of information into a single joint risk distribution and determine the weight that each data element should have in the joint distribution.

Modelling operational risk dependencies

As the ORMS matures with improved data quality and a well-trained modelling team, the institution may decide to implement a more precise modelling of operational risk dependencies. This allows it to acquire a better understanding of common drivers of operational risk events, more precise capital allocation and, potentially, capital savings.

Nevertheless, the calculation of operational risk dependencies presents several challenges, which include the definition of a correlation framework with a dimension consistent with the amount of data available; data series arrangement and mitigating the data non-linearity; seasonality; and limited data availability (see Chapters 6 and 7). Also, the determination and replication of a dependency between severity and frequency dependency require the use of nonstandard correlation calculation and simulation methods (see Chapter 8).

Technology supporting the modelling process

As a result of the challenges presented above, operational risk modellers need to establish multiple analytical documentation and control processes to determine and justify operational capital results and guarantee their governance. Given the absence of widely accepted modelling standards, models are too frequently based on bespoke tools,[3] which frequently lack adequate data integrity, audit trail, automatic assumption documentation and interfaces with data sources and uses, as well as displaying other weaknesses.

The use of these types of limited bespoke tools induces more

time-consuming modelling, maintenance and documentation, increases model error and makes the knowledge transfer of model functioning and methodology more difficult. Also, it becomes very hard to implement any change in model parameters or rerun the model under different assumptions. As a result, the institution develops strong dependence on the group of specialists who have developed the model and, in addition, may not have the adequate governance over the capital modelling process.

The technology supporting the modelling represents, last but not least, the very significant challenge of operational risk capital modelling. It is worthy of note that the use of the appropriate technology facilitates the implementation of all the methods and analytics described in this work into a highly doable task requiring a reasonable number of resources, thanks to the elimination of non-value-added manual tasks.

REGULATORY COMPLIANCE AND SUPERVISION OF THE OPERATIONAL RISK CAPITAL MODEL

The challenges of extreme event modelling with little historical and relevant data, forward-looking estimates and so on are shared with many areas of science, such as actuarial pricing, electronics and nuclear energy. However, when these challenges are involved in financial institutions' solvency reporting, a potential conflict of interest emerges: while capital is scarce and expensive for financial institutions, lenders and investors need these financial institutions to have sufficient capital for solid solvency. In fact, the solvency level of the institution will have a direct impact on the institution's financing costs and financial results.

To guarantee that this conflict of interest does not influence capital determination in any institution, an independent review and approval of the model is performed by supervisors. Here, the supervisory role is to ensure that capital calculation is not only acceptable for internal use, but also satisfactory as a solvency measure for external parties.

It follows that the modelling should incorporate governance processes, as a means of reassuring supervisors and external parties with the capital results and calculation processes. For the reassurance and model approval, supervisors across countries and industries share expectations such as the following:

- Robust processes to capture and determine capital modelling inputs: The quality of capital estimations is fully dependent on the inputs to the model. Therefore, supervisors expect institutions to have implemented solid collection and determination processes for internal loss data, external data and scenario analysis, and business environment and internal control factors (see Chapter 2).
- Audit trail of data sources and their transformations: To validate capital model results, all data sources and their transformations, additions and so on need to be thoroughly documented, so as to permit the replication of the modelling sample used and the capital results. Figure 1.6 shows an example of how to trail and document modelling assumptions.
- Solid justification and documentation of modelling assumptions: The selection of distribution type, fitting method, modelling threshold, data elements aggregation method, correlations and so on should be solidly justified and documented (see Part II, "General Framework for Operational Risk Capital Modelling"). Extensive documents and illustrations describing the analysis performed and modelling decisions taken need to be created in order to adequately justify modelling decisions to supervisors.
- Consistency of modelling criteria: The practitioner should apply the same criteria in modelling all risk types and BUs without directing the modelling to obtain a specific result. Modelling consistency can be documented by detailed workflows describing the analysis step by step and the decisions taken at each step.

Figure 1.6 Audit trail of operational risk modelling

	User	Operation type	Time	Date	Application module	Data Origin	Operation Data	Operation Details
1	Rafa...	Create Audit Trail	18:20	19/12/2013	Scenario modeling			
2	Rafa...	Read data	18:20	19/12/2013	Scenario modeling	GRC Scen...	Read data info	
3	Rafa...	Select data	18:20	19/12/2013	Scenario modeling	APPLICATI...	Risk of costs of...	
4	Rafa...	Data Modify	18:20	19/12/2013	Fit Quant	Application	FIT	
5	Rafa...	Data Modify	18:21	19/12/2013	Fit Quant	Database	SET	Set Skewness (5.100000e+000)and Kurtosis (33) from data...
6	Rafa...	Data Modify	18:21	19/12/2013	Fit Quant	Application	FIT	
7	Rafa...	Data Modify	18:21	19/12/2013	Fit Quant	User	SET	Stress frequency to NaN
8	Rafa...	Data Modify	18:21	19/12/2013	Fit Quant	User	SET	Stress severity to 30
9	Rafa...	Data Modify	18:21	19/12/2013	Fit Quant	Application	FIT STRESS SEV	
10	Rafa...	Data Modify	18:22	19/12/2013	Fit Quant	User	SET	Mean to 700
11	Rafa...	Data Modify	18:22	19/12/2013	Fit Quant	Application	FIT STRESS SEV	

- Analysis of capital estimates stability: The modelling quality and forward-looking nature of the capital estimations receive a solid evaluation by the analysis of the capital results stability (see Chapter 4).
- Capital results validation process: Results of capital estimations acquire additional support when they are validated against losses occurring after the modelling date with techniques such as backtesting to verify the adequateness of distribution assumptions etc.
- Full understanding of the modelling process and methodology: The institution needs to fully understand the complexities of the modelling process. It follows that the complexity of the analytical processes has to be in accordance with the institution resources, knowledge and experience. In fact, institutions generally start modelling with simpler approaches – for instance, only internal-loss-data-based – and, as experience is gained, they incorporate additional inputs such as external data and scenario analysis. When technology is assisting the modelling, black boxes should be avoided and the institution should have access to and fully understand the modelling code.
- User control and approvals: When multiple BUs, departments or modellers participate in the input collection and model building, control and audit over contributors helps in governing the model. Also, validations and approvals over different steps of the modelling constitute a solid control the modelling process.

Many of these supervisory expectations add significant efforts and challenges to the internal operational risk modelling process.

An additional element of governance by supervisors is the use test. This means that capital estimations should be embedded within decision-making practices and on an ongoing business-as-usual basis. Supervisors expect financial institutions to accept and trust the capital estimations so that they can be used in their daily decisions. If a capital determination process is related only to regulatory compliance, the institution may be tempted to underestimate capital charges.

In fact, BCSG-AMA explicitly says, "The purpose and use of an AMA should not be solely for regulatory compliance purposes." Also, the regulatory approval of a capital model implies that the institution has developed a risk-based management, which provides

additional trust in the institution's capacity to mitigate risks. It follows that operational risk modelling results should be embedded in the risk mitigation investment evaluation, performance measurement, financial budgeting, resource allocation, strategic plan definition, etc.

The advanced approach for capital calculation, together with the use test, creates a strong virtuous circle for operational risk management. The required data elements for its implementation provide an understanding of the risk profile, permitting a thorough risk mitigation. The fact that the inputs to the capital model are also used for mitigation incentivises a much deeper analysis, thus improving, in turn, the quality of the inputs to the capital model. This virtuous circle is probably the largest benefit an institution may get from an advanced approach for operational risk capital calculation. Indeed, it is uncommon to see such systematic and thorough operational risk mitigation in financial institutions calculating operational risk capital under standard or basic indicator approaches. This suggests that the advanced approach represents a very strong stimulus for solid operational risk mitigation.

Embedding capital results into the day-to-day risk management requires the development of strong analytical and management processes, see Part III.

The evaluation of risk mitigation investment requires the implementation of financial analysis incorporating operational risk capital. The evaluation of insurance requires the modelling of all insurance features, limitations and so forth into the operational loss simulation. Embedding the capital calculations into the performance management, financial budgeting and so on requires the integration of operational risk capital into the rest of the economic capital programme.

Finally, from the technology perspective, supervisors expect that it should minimise model error and facilitate timely modelling and assumption documentation and an effective enforcement of model governance. Model error is minimised through an optimal integrity of data flows and the automation of analytical and documentation processes. Model governance is facilitated with audit trail and user control functionalities embedded in operational risk management and modelling technology.

All these requirements are, either explicitly or implicitly, included

in the previously mentioned Basel Committee on Banking Supervision's "Operational Risk – Supervisory Guidelines for Advanced Measurement Approaches" (BCSG-AMA). The focus of this work is to address aspects more closely related to the modelling (and data collection, preparation and statistical processes) of capital. Table 1.1 summarises the different requirements of the Basel Committee document and how the chapters of this work can help to address them. Needless to say, however, the final regulatory approval of an operational risk capital model will eventually depend on the views, evaluations, negotiations and final discretion of the relevant national supervisor.

Table 1.1 Supervisory requirements and sections of this work

Supervisory quotation	**Part or chapter of this Book**
Model Inputs	
"An AMA for calculating the operational risk capital charge of a bank requires the use of four data elements which are: (1) internal loss data (ILD); (2) external data (ED); (3) scenario analysis (SBA) and (4) business environment and internal control factors (BEICFs)."	Part I, "Capture and Determination of the Four Data Elements" Part II, "General Framework for Operational Risk Capital Modelling"
"The purpose of the standards is to provide insight into supervisors' minimum expectations regarding data integrity and comprehensiveness, both of which are critical to the effective implementation of an AMA."	Part I, "Capture and Determination of the Four Data Elements"
"To maintain consistency, a bank should develop data policies and procedures that include, for example, guidelines around perimeter of application, minimum observation period, reference date, de minimis modelling thresholds, and data treatment."	Part I, "Capture and Determination of the Four Data Elements"
Modelling assumptions	
"Supervisors expect ILD to be used in the operational risk measurement system (ORMS) to assist in the estimation of loss frequencies; to inform the severity distribution(s) to the extent possible."	Chapter 2, "Collection of Operational Loss Data" Chapter 4, "Loss Data Modelling"
"In accordance with paragraph 669(c) of the Basel II Framework, an AMA bank's risk measurement system 'must be sufficiently granular to capture the major drivers of operational risk affecting the shape of the tail of the loss estimates'."	Chapter 4, "Loss Data Modelling"
"The bank should put in place methodologies to reduce estimate variability and provide measures of the error around these estimates (eg confidence intervals, *p*-values)."	Chapter 4, "Loss Data Modelling"
"It generates a loss distribution with a realistic capital requirements estimate, without the need to implement 'corrective adjustments' such as caps."	Chapter 4, "Loss Data Modelling"

Supervisory quotation	Part or chapter of this Book
"Supervisors expect ED to be used in the estimation of loss severity as ED contains valuable information to inform the tail of the loss distribution(s)."	Chapter 2, "Collection of Operational Loss Data: ILD and ED" Chapter 4, "Loss Data Modelling: ILD and ED"
"A data scaling process involves the adjustment of loss amounts reported in external data to fit a bank's business activities and risk profile. Any scaling process should be systematic, statistically supported, and should provide output that is consistent with the bank's risk profile."	Chapter 4, "Loss Data Modelling: ILD and ED"
"A robust scenario analysis framework is an important element of the ORMF. This scenario process will necessarily be informed by relevant ILD, ED and suitable measures of BEICFs."	Chapter 3, "Scenario Analysis Framework and BEICFs Integration" Chapter 5, "Scenario Analysis Modelling"
"A bank should thus ensure that the loss distribution(s) chosen to model scenario analysis estimates adequately represent(s) its risk profile."	Chapter 5, "Scenario Analysis Modelling"
"A robust governance framework surrounding the scenario process is essential to ensure the integrity and consistency of the estimates produced."	Chapter 3, "Scenario Analysis Framework and BEICFs Integration"
"BEICFs are operational risk management indicators that provide forward-looking assessments of business risk factors as well as a bank's internal control environment."	Chapter 3, "Scenario Analysis Framework and BEICFs Integration" Chapter 6, "BEICFs Modelling and Integration into Capital Model"
"The bank should follow a well specified, documented and traceable process for the selection, update and review of probability distributions and the estimate of its parameters."	Chapter 4, "Loss Data Modelling: ILD and ED"
"A bank should carefully consider how the data elements are combined and used to ensure that the bank's operational risk capital charge is commensurate with its level of risk exposure."	Chapter 7, "Hybrid Model Construction: Integration of ILD, ED and SA"
"The combination of data elements should be based on a sound statistical methodology."	Chapter 7, "Hybrid Model Construction: Integration of ILD, ED and SA"
"The techniques to determine the aggregated loss distributions should ensure adequate levels of precision and stability of the risk measures."	Chapter 7, "Hybrid Model Construction: Integration of ILD, ED and SA"
"A bank should pay particular attention to the positive skewness and, above all, leptokurtosis of the data when selecting a severity distribution."	Chapter 4, "The Scale and Shape Scaling Method" Chapter 5, "Scenario Analysis Modelling"
"When separate distributions for the body and the tail are used, a bank should carefully consider the choice of the body-tail modelling threshold that distinguishes the two regions."	Chapter 4, "Loss Data Modelling: ILD and ED"
"As such, simulation, numerical or approximation methods are necessary to derive aggregated curves (e.g. Monte Carlo simulations, Fourier Transform-related methods, Panjer algorithm and Single Loss Approximations)."	Chapter 8, "Derivation of the Joint Distribution and Capitalisation of Operational Risk"

Supervisory quotation	Part or chapter of this Book
"Robust estimation methods (such as alternatives to classical methods as the Maximum Likelihood and the Probability Weighted Moments), proposed recently in operational risk literature, are reasonably efficient under small deviations from the assumed model."	Chapter 4, "Loss Data Modelling: ILD and ED"
"A bank should assess the quality of fit between the data and the selected distribution. The tools typically adopted for this purpose are graphical methods (which visualise the difference between the empirical and theoretical functions) and quantitative methods, based on goodness-of-fit tests. In selecting these tools, a bank should give preference to graphical methods and goodness-of-fit tests that are more sensitive to the tail than to the body of the data (e.g. the Anderson Darling upper tail test)."	Chapter 4, "Loss Data Modelling: ILD and ED"
"Moreover, the results of the goodness-of-fit tests are usually sensitive to the sample size and the number of parameters estimated. In such cases, a bank should consider selection methods that use the relative performance of the distributions at different confidence levels. Examples of selection methods may include the Likelihood Ratio, the Schwarz Bayesian Criterion and the Violation Ratio."	Chapter 4, "Loss Data Modelling: ILD and ED"
"The bank may be permitted to use internally determined correlations in operational risk losses across individual operational risk estimates, provided it can demonstrate to the satisfaction of the national supervisor that its systems for determining correlations are sound, implemented with integrity and take into account the uncertainty surrounding any such correlation estimates (particularly in periods of stress). The bank must validate its correlation assumptions using appropriate quantitative."	Chapter 8, "Derivation of the Joint Distribution and Capitalisation of Operational Risk"
"A bank should also gather information on the expected loss. Due to its high sensitivity to extreme losses, the arithmetic mean can cause an inaccurate picture for the expected losses. In light of this, the use of statistics that are less influenced by extreme losses (e.g. median, trimmed mean) is recommended, especially in the case of medium/heavy tailed datasets."	Chapter 8, "Derivation of the Joint Distribution and Capitalisation of Operational Risk"
"Whatever approach is used, a bank must demonstrate that its operational risk measure meets a soundness standard comparable to that of the internal ratings-based approach for credit risk (ie comparable to a one year holding period and a 99.9th percentile confidence interval)."	Chapter 8, "Derivation of the Joint Distribution and Capitalisation of Operational Risk"
"However, a bank must be able to demonstrate that its approach captures potentially severe 'tail' loss events."	Chapter 4, "Loss Data Modelling: ILD and ED" Appendix I, "Distributions for Modelling Operational Risk Capital"
"Exploratory Data Analysis (EDA) for each ORC to better understand the statistical profile of the data and select the most appropriate distribution …	Chapter 4, "Loss Data Modelling: ILD and ED"
"Appropriate techniques for the estimation of the distributional parameters; ..."	Chapter 4, "Loss Data Modelling: ILD and ED"
"Appropriate diagnostic tools for evaluating the quality of the fit of the distributions to the data, giving preference to those most sensitive to the tail."	Chapter 4, "Loss Data Modelling: ILD and ED"

Supervisory quotation	Part or chapter of this Book
"Capital allocation to internal business lines should be a factor when choosing ORCs, as these ORCs may be used as part of the capital allocation process."	Chapter 8, "Derivation of the Joint Distribution and Capitalisation of Operational Risk" Chapter 1, "BEICFs Modelling and Integration into Capital Model"
"Moreover, a bank should perform sensitivity analyses and stress testing (e.g. different parameter values, different correlation models) on the effect of alternative dependence assumptions on its operational risk capital charge estimate.	Chapter 2, "Backtesting, Stress Testing and Sensitivity Analysis"
Verification and validation	
"Verification of the ORMF includes testing whether all material aspects of the ORMF have been implemented effectively …: … a comparison of scenario results with internal loss data and external data."	Chapter 3, "Scenario Analysis Framework and BEICFs Integration"
"Validation ensures that the ORMS used by the bank is sufficiently robust and provides assurance of the integrity of inputs, assumptions, processes and outputs."	This work focuses in the modelling. However, in the introduction we mention these topics in: This chapter, "Regulatory compliance and supervision of the operational risk capital model" Chapter 4, "Backtesting, Stress Testing and Sensitivity Analysis"
"Verification activities test the effectiveness of the overall ORMF, consistent with policies approved by the board of directors, and also test ORMS validation processes to ensure they are independent and implemented in a manner consistent with established bank policies."	
"Results from verification and validation work should be documented and distributed to appropriate business line management, internal audit, the corporate operational risk management function and appropriate risk committees. Bank staff ultimately responsible for the validated units should have access to, and an understanding of, these results".	
"The validation process of the ORMS should provide enhanced assurance that the measurement methodology results in an operational risk capital charge that credibly reflects the operational risk profile of the bank."	Chapter 5, "Backtesting, Stress Testing and Sensitivity Analysis"
Use test	
"The bank should have adequate processes in place to monitor identified controls, ensuring that they are appropriate to mitigate the identified risks to the desired residual level and operating effectively."	Chapter 6, "Risk–Reward Evaluation of the Mitigation and Control Effectiveness"
"A bank´s board of directors should approve and review a clear statement of operational risk appetite and tolerance."	Chapter 7, "Strategic and Operational Business Planning and Monitoring"
"A bank´s strategic and business planning process should consider its operational risk profile, including outputs from the ORMS."	Chapter 8, "Strategic and Operational Business Planning and Monitoring"

1 We refer to operational risk capital bottom-up models such as LDA, SBA and hybrid models. In financial industry regulation, this type of model is called AMA (advanced measurement approach) in Basel II/III and internal models in Solvency II.

2 In this book, all graphs and calculations referring to capital modelling have been performed using OpCapital Analytics, a software solution based on MatLab specifically designed for the calculation of operational risk capital requirements under advanced approaches.

3 Bespoke models refer to those created in-house with limited use of GUIs and data sources' interphases, suboptimal integrated flows, limited reporting capabilities and scarce model governance such as nonexistence of audit trail or user control.

REFERENCES

Robertson, Douglas, 2011, "So That's Operational Risk!", OCC Economics Working Paper 2011-1, March.