Practical methods of modelling operational risk

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ABSTRACT
With regulatory frameworks for banks and insurers requiring capital to be held against operational risk losses, greater focus is being placed on the modelling of operational risk – comparable to the modelling efforts on market, credit and insurance risk. Several factors make the modelling of operational risk particularly difficult. This category of risk includes a wide range of disparate risks requiring different modelling techniques. Financial institutions typically do not have sufficient historical data and where adequate data is available, the data seldom include events from the tails of the underlying distributions. The interaction of the different operational risk sub-categories with each other and other risk types is complex to model. However, many banks and insurers develop and use operational risk models. This paper surveys the literature and publicly disclosed information on operational risk modelling and summarises the main methods employed in practice. The paper aims to explain the modelling of operational risk in practical terms and does not focus on the advanced mathematical and statistical methods employed in the modelling process. The paper includes simulated numerical examples to demonstrate the sensitivity of the resulting capital to certain modelling assumptions.

KEYWORDS
Operational risk; loss distribution approach

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1. INTRODUCTION

1.1 Capital requirements for banks and insurers now require capital to be held against operational risk losses. Banks typically have advanced methods for modelling market and credit risk whereas most insurers have a detailed understanding of insurance risk and where required, market and credit risk. The capabilities and data to model operational risk have until recently not been available. The capital charge for operational risk compared to capital for others risks emphasises how significant this risk class can be. Estimates for banks are that 60% of regulatory capital can be allocated to credit risk, 15% to market risk and 25% to operational risk. The QIS2 results\(^1\) show that operational risk capital accounted for 6% of the Solvency Capital Requirement (SCR) for life insurers and 8% of the SCR for non-life insurers. When trying to understand the quantum of this number, many financial institutions realise how little they know about this risk category. The journey to model operational risk capital is often a first step in the understanding of operational risk.

1.2 This paper gives a high-level overview of the current state of the modelling of operational risk. This paper focuses on the implication for insurers, but as banks are much further along the journey a lot of reference will be made to operational risk modelling in banking. In section 2 the definition of operational risk is discussed as consistent definition drives data collection which is critical for accurate modelling. Section 3 looks at the various regulatory requirements requiring different financial institutions to hold capital against operational risk losses. In section 4 some of the reasons why financial institutions may consider the advanced modelling of operational risk are discussed. Section 5 gives a high-level overview of the methods available to model operational risk, and section 6 discusses the Loss Distribution Approach, which is widely used in the banking world, in some detail. In section 7 the results of two simulation studies are discussed. The first one highlights the importance of adjusting standard fitting methods for truncation of the data and the second one highlights the need to improve the confidence of scenario-based models with data. Section 8 concludes.

2. DEFINITION OF OPERATIONAL RISK

2.1 The actuarial control cycle has been ingrained in actuaries through our training. The iterative process of defining a problem, designing a solution and then monitoring the results also applies to risk management. An important risk category has until recently been left out of this cycle, partly due to the difficulty in defining the risk.

2.2 Whereas market risk, credit risk and insurance risks are easy to define and to measure, operational risk remains more elusive. In earlier papers on risk management for banks, operational risk was a catchall category including all the risks not included

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\(^1\) https://www.fsb.co.za/Departments/insurance/Documents/SAM_SA_QIS2_Report.pdf
in market and credit risk. With the Basel II accord came a tighter, formal definition of operational risk together with the requirement to hold capital against this risk. According to this definition, operational risk is the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events. This includes legal risk, but excludes strategic or reputational risk (BIS, unpublished b). This definition is now pervasive in text books and papers and has also been adopted in the proposed Solvency II framework in Europe and the proposed Solvency Assessment and Management (SAM) insurance regulation in South Africa.

2.3 From this definition it can be seen that operational risk includes risks caused by the internal circumstances of the firm and risks caused by external events.

2.4 The Basel II Accord further categorises operational risk into six loss types and seven event types spread over eight business lines (BIS, unpublished b). The seven event types are:

— internal fraud;
— external fraud;
— employment practices and workplace safety;
— clients, products and business practices;
— damage to physical assets;
— business disruption and systems failures; and
— execution, delivery and process management.

2.5 Although it could be argued that this classification is not appropriate for insurers, it is possible to apply this classification to insurers. Cooper, Piwcwics & Warren (unpublished) gives insurance-specific examples of events that would fall into each of these categories. Tripp et al. (2004) uses a system where the cause, event and consequences of each loss is considered to attribute losses accurately to operational risk and avoid double counting and omission.

2.6 The FSA (unpublished) gives a list of factors that insurers must consider when assessing operational risk quoted here in full:

Examples of some issues that a firm might want to consider include:

1) the likelihood of fraudulent activity occurring that may impact upon the financial or operational aspects of the firm;

2) the obligation a firm may have to fund a pension scheme for its employees;

3) the technological risks that the firm may be exposed to regarding its operations. For example, risks relating to both the hardware systems and the software utilised to run those systems;

4) the reputational risks to which the firm is exposed. For example, the impact on the firm if the firm’s brand is damaged resulting in a loss of policyholders from the underwriting portfolio;
5) the marketing and distribution risks that the firm may be exposed to. For example, the dependency on intermediary business or a firm’s own sales force;
6) the impact of legal risks. For example a non-insurance related legal action being pursued against the firm;
7) the management of employees – for instance staff strikes, where dissatisfied staff may withdraw goodwill and may indulge in fraud or acts giving rise to reputational loss;
8) the resourcing of key functions such as the risk management function by staff in appropriate numbers and with an appropriate mix of skills such as underwriting, claims handling, accounting, actuarial and legal expertise;

2.7 An industry study of American and Canadian insurers (Acharrya, 2012) shows that given the different nature of banking and insurance, operational risk could be considered as less of a concern for insurers. The nature of banking is much more transactional whereas insurance is more long-term and strategic.

2.8 Although the definition of operational risk and the classification of different losses and events may sound trivial this will drive data collection attempts. For industry-wide data collection schemes it is of utmost importance that a common classification emerges in the insurance industry. Further work is required to determine whether the Basel categorisation makes sense for the unique circumstances of insurers.

3. REGULATORY REQUIREMENTS
3.1 The focus on operational risk as a risk class has been reinforced by the requirement in the Basel II accord for banks to hold capital against operational risk losses by the end of 2006. Banks can use one of the following approaches to quantify operational risk: the Basic Indicator Approach, the Standardised Approach or the Advanced Measurement Approach (AMA). Three different AMAs, namely the Internal Measurement Approach, the Loss Distribution Approach (LDA) and the Scorecard Approach are suggested. There are various regulatory approvals required and tests that banks must pass before they are allowed to use their own internal models to set regulatory capital for operational risk. The LDA is a statistical approach which entails the fitting of distributions to data to inform the capital charge and will form the basis of the discussion in the rest of the paper.

3.2 In South Africa, the South African Reserve Bank implemented Basel II and hence required banks to hold capital against operational risk capital from 1 January 2008.

3.3 A similar requirement was introduced for life insurers for the first time in 2008 with the seventh revision of the Actuarial Society of South Africa’s Standard
of Actuarial Practice 104. Whereas the other components of the Capital Adequacy Requirement (CAR) specified by the guidance are based on prescribed formulae, the operational risk component of the CAR requires that “the Statutory Actuary must ensure that an appropriate level of capital is held to cover operational risk”.\(^2\) The Basel II definition of operational risk is used in this guidance. For short term insurers, the Financial Services Board’s Board Notice 169 of 2011 introduced a requirement to hold capital against operational risks. A formula for the calculation is prescribed.\(^3\)

3.4 The Financial Services Authority (FSA) has introduced an Individual Capital Adequacy Standard for insurance companies in the Prudential Sourcebook in 2004. The guidance include six categories of risk insurers must consider, one of which is operational risk.

3.5 Under the proposed Solvency II and SAM frameworks insurers have to hold capital against operational risk losses. The standard formula for the SCR gives a specified formula for calculating the capital for operational risk. The capital is calculated as a percentage of premiums or technical provisions subject to a maximum of 30% of the capital for other risks for all business excluding unit-linked life business.\(^4\) For unit-linked life business the capital is set as 25% of the expenses for such business. Under both these regimes insurers can choose to calculate their regulatory capital using an approved internal model or a partial internal model covering certain risks or parameters. Similar to Basel II, insurers are given the choice to build their own capital model and therefore have the choice to build their own capital model for operational risk.

4. **POSSIBLE REASONS FOR ADVANCED MODELLING OF OPERATIONAL RISK**

4.1 A possible motivation for many banks and insurers to model operational risk is the prospect of a reduction in capital. Even more important than this are the many business benefits derived from having a better understanding of operational risk. The QIS2 results\(^5\) give some feedback from insurers on the standard formula for operational risk capital. Some of the comments were that the operational risk formula is not risk-sensitive and does not take business-specific considerations into account. Linked insurers were concerned with the link between operational expenses and operational risk capital. The formula specified by QIS3 remained largely unchanged.

4.2 The modelling of operational risk focuses the minds of risk management professionals and also operational management on operational risk. This improved


understanding of operational risk gives management the opportunity to make informed decisions about the best way to deal with each risk classified as an operational risk. Various options are available:

— The organisation can decide to accept the risk at the current level of control.
— The organisation can purchase insurance against the losses resulting from the risk.
— The organisation can take specific actions or change their business practices to eliminate or reduce the risk.

4.3 It is important to note that the adequacy and effectiveness of such mitigating actions need to be considered and that there may remain some residual risk after allowing for these actions. Operational risk models can be used to quantify the impact of the effectiveness of these measures as they are much more flexible than standard formulae. Such models are therefore beneficial even if financial institutions do not go through the formal process to apply to use the model for setting regulatory capital.

4.4 A further question is whether holding capital is an appropriate response to protect a financial institution against operational risk losses. Dexter et al. (2007) give possible reasons why it may not be appropriate to hold capital against operational risk losses. Capital is only required against risks that impact items on the solvency balance sheet. Some risks do not impact the balance sheet. This is the reason why reputational risk is excluded from operational risk as goodwill or franchise value is not generally included as an asset on the solvency balance sheet, and hence it is not required to hold capital against events that can lead to the destruction of such value. It is possible that the impact of some operational risks may be covered elsewhere in the capital. As an example, operational risk losses may have been classified as claims or expenses and through this incorrect classification affected the calibration of the modules to calculate capital for these risks. It is also possible that the impact of some operational risks may be immaterial and can therefore be excluded.

4.5 It should be noted that the QIS3 technical specification explicitly states the operational risk module is intended to allow for operational risks not explicitly covered in other risk modules.⁶

5. METHODS FOR MODELLING OPERATIONAL RISK
5.1 Various methods are used in practice to determine operational risk capital. Lam (2003) discusses top-down approaches for calculating operational risk capital. If the total capital for the business is known, then the capital for other risks can be subtracted to give the operational risk capital. It is however not clear how the total capital should

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be determined. Various bottom-up approaches are available for calculating operational risk capital from the driving factors as discussed in the following paragraphs.

5.2 Under standard formulae approaches a simple formula is specified which typically specifies operational risk capital as a percentage of an indicator representing a volume measure of the business such as premiums or gross income. The Basic Indicator Approach under Basel II and the operational risk component of the SCR using the standard formula under Solvency II and SAM are examples of standard formulae approaches. More complex approaches such as the Standardised Approach under Basel II allows different indicators and percentages to be used for different business lines.

5.3 The internal measurement approach is the first of the AMAs given by Basel II and is an intermediate step towards the more advanced approaches. While the method for calculating operational risk capital is specified insurers can use internal loss data to calibrate the parameters used. This approach was introduced to give banks the incentive to collect loss data.

5.4 LDA is a statistical approach under which a distribution is fitted to each operational risk category. The capital charge is taken as a percentile from these distributions and different methods are used to aggregate the capital from different operational risk categories.

5.5 Under the scorecard approach the capital is calculated by applying a risk score to different exposure indicators. The challenge lies in building an appropriate forward-looking scorecard. The initial level of capital will often be based on historical loss data using methods similar to the LDA, but the added advantage of this method is that it is more forward-looking.

5.6 More advanced methods exist. One such example discussed in Tripp et al. (op. cit.) is the method of Bayesian causal networks. This method requires a causal map to be set up for operational risk events. Probabilities are assigned to different causes and Bayesian techniques used to determine an overall probability. The probabilities need to be combined with a risk indicator to produce a capital charge.

5.7 The remainder of this paper will deal with the LDA approach as this is the approach most common in the banking world and is widely used in the insurance sector. However, it should be noted that banks are many years ahead in the collection of loss data.
6. THE LDA APPROACH
6.1 The LDA Approach at a Glance
6.1.1 This section describes the LDA approach at a high level. The remainder of the paper will deal with the different components of the LDA in more detail.

6.1.2 Operational risk loss data is divided into homogeneous operational risk categories based on the risk event type and business unit or geographical location. Where insufficient internal or external loss data is available for a certain category, the data may be supplemented by scenario analysis. Where no or little data is available the approach can be based entirely on scenarios. A distribution is fitted to the data for each category. Using the actuarial frequency/severity approach used to model claims in short-term insurance, a compound distribution is usually fitted to the data. An appropriate discrete distribution is used for the frequency and a continuous distribution for the severity of the claims. As such compound distributions are not easily solved analytically, Monte Carlo simulation is used to find the overall distribution function for each category. The capital for each category is then set equal to the desired percentile from the fitted distribution. An important consideration is how to combine the capital from different operational risk categories. A possible way of modelling the correlation is to use a copula approach. Under this approach a joint distribution for all the categories are obtained. Again Monte Carlo simulation will be used to find the distribution function from which the desired percentile is used as the capital. Finally, consideration should be given how to combine the capital for operational risk with capital for other risks. This can either be done by adding the capital for operational risk with the capital charges for the other risks or by allowing for correlation.

6.1.3 In the preceding paragraph the capital was described as a percentile from the loss distribution. However, careful consideration should be given to what capital needs to be held for operational risk. A value-at-risk approach is usually used for capital which requires a time horizon and a confidence level to be specified. For an insurer, capital for market and insurance risk is typically calculated as the difference between the percentile at the desired level of confidence and the expected value of the distribution. This is because the expected value is allowed for in the liabilities (technical provisions). When modelling operational risk one should determine whether liabilities already allow for the expected value of losses.

6.1.4 The remainder of this section discusses the intricacies of this approach in more detail.

6.2 Data
6.2.1 Introduction
6.2.1.1 The LDA is very dependent on the availability of data as the approach involves the fitting of distributions. The lack of data as well as the features of the available data will shape the approach used to a large extent. In choosing the number of operational risk categories to model, one should balance the requirement to model homogeneous risks with having sufficient data in each category to perform statistical analysis.
6.2.1.2 As with any actuarial problem, a starting point for setting future experience is the analysis of past data. This immediately poses problems for most insurers as many insurers have not been recording operational risk losses over a long enough period to have sufficient, credible internal data. Not only does this restrict the availability of internal data, but further limits the data that can be supplied to industry-wide data collection schemes. It is also possible that the data is not granular enough to allocate the losses to the different operational risk categories. Even where ample data is available it is unlikely that the data will include many events in the tail and for capital being set at a 99.5th or 99.9th percentile level, the tail of the distribution is particularly important. The next section will deal with how internal data can be supplemented by appropriate external data or scenario analysis.

6.2.1.3 Embrechts, Furrer & Kaufman (2003) show the number of losses required to accurately fit a distribution is determined by the type of distribution fitted as well as the percentile. A few hundred observations are typically required and for many operational risk categories this is unlikely to be available.

6.2.1.4 The AMA under Basel II require the use of four data elements, namely internal loss data, external data, scenario analysis and business environment, and internal control factors. These four elements will be discussed in more detail in the following sections.

6.2.2 **Internal Loss Data**

6.2.2.1 When a financial institution embarks on the journey to model operational risk, a first step must be to determine what loss data have been recorded by the organisation in the past. Certain high frequency/low severity operational losses (such as transactional errors) may already be recorded and tracked. There may be some institutional memory about big losses that can be manually included in data. However, these will only provide a first step in the data collection journey.

6.2.2.2 In order to make sure that sufficient data is available at some stage in future for modelling purposes, a clear data collection framework must be rolled out throughout the business. The framework must give clear guidance about the following:

— The details of the loss that must be recorded in order to enable modelling. Careful consideration should be given to which details must be recorded to ensure that all the details required for correct classification (and potentially future industry data collection initiatives) are recorded.

— Typically only losses above a certain threshold will be recorded. This threshold must be carefully selected and consistently applied as it can significantly affect the modelling and lead to bias in the capital figure.

— How data must be grouped should be specified. Generally ungrouped data is desirable, but there could be a single operational risk event leading to many small losses, e.g. a computer failure leading to many incorrect balances.

— The definition of the actual gross loss must be given. For example certain operational risk events may lead to higher claims, higher expenses, increases in
liabilities or a fall in asset values. Clear guidance is necessary how to account for each of these in the operational risk database.
— Details must be supplied on how to record recoveries from insurance and the impact of other risk mitigation strategies or controls if available.
— There should be guidance on how to record near miss events, as these can provide valuable information. Such events would be instances where the event was identified and the situation resolved before an actual loss was incurred.

All of this will have to be carefully considered as not having any of the detail available can greatly hamper the modelling.

6.2.2.3 The recording must be consistently applied throughout the organisation. This becomes even more challenging for financial institutions with many diverse business units operating in different geographical areas. Managers may also be reluctant to record losses that may reflect poorly on their performance or the performance of their business units. All of this must be covered by policies with appropriate controls around the process to ensure the integrity of the internal loss data.

6.2.2.4 Consideration will have to be given during the modelling stage as to whether the data is an accurate guide for future experience. People, processes, controls and the external environment can change significantly over time and given the divergent nature of operational risk these can significantly impact future experience.

6.2.2.5 The impact of inflation on the recorded losses will also have to be allowed for in the modelling.

6.2.2.6 Dexter et al. (op. cit.) discuss several reservations with the usefulness of internal data. One of the main problems is that the events required to accurately fit the tail of the distributions which is what determines the capital at a high percentile is rare and will probably not be included in the dataset.

6.2.3 External Data

6.2.3.1 ILD can be supplemented by external data. Various databases exist focusing mostly on operational risk loss data for banks. Martin & Hayes (2013) give a list of the main databases such as the ORX database, British Bankers’ Association GOLD and Algo First. The Association of British Insurer’s ORIC database is thus far the only consortium for insurers. Their website show that their membership includes at least two South African insurers at the time of writing.7 Martin & Hayes (op. cit.) further show that at least 86% of South African insurers surveyed would be interested in subscribing to a South African operational risk consortium for insurers.

6.2.3.2 How financial institutions use external data varies greatly: some only use external data as an input to inform scenario analysis, others blend internal and external data while other may base their modelling for certain ORCs entirely on external data.

6.2.3.3 All the issues discussed in the section on ILD are also relevant for external data.

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7 https://www.oricinternational.com/membership/current-members/
data. As the recording of external data is not under the direct influence of the financial institution it becomes very important to understand how each of the items listed in the section on internal loss data have been treated. As this data combine information from many different sources it may not be possible to get all the required information and in many instances different rules may have been applied by different contributors.

6.2.3.4 A potential source of bias in external data, as discussed in de Fontnouvelle et al. (unpublished), is that it may include a disproportionate number of large losses. Typically large losses are reported in the media and are more likely to be reported to data collection schemes than smaller losses which are not in the public domain.

6.2.3.5 BIS (unpublished a) requires banks to scale external data to fit the bank’s risk profile. Financial institutions need to find a way to translate data from institutions with very different sizes, risks and controls to be applicable to their own business. Other authors such as Frachot, Moudoulaud & Rocalli (2004) (referred to as FMR) believe that scaling is not practical given the large data requirements to do this properly.

6.2.4 Scenario Analysis

6.2.4.1 An important input into the operational risk modelling process is scenario data, which are typically collected from the business and represent the losses at selected percentiles for the relevant category of risk.

6.2.4.2 These data are particularly useful where there is not sufficient internal loss data or external data for a certain category. Even when there are sufficient data for credible modelling there may not be any losses from the tail of the distribution included in the data. Where financial institutions have reason to believe that past losses are not an accurate reflection of likely future losses, scenarios can allow for such changes in the business. The scenario setting process also has the advantage of involving line managers from different departments in the operational risk modelling process and will give them a much better understanding of the modelling process, the resulting capital allocated to their business units and the impact of different actions on the operational risk profile of the organisation.

6.2.4.3 Dexter et al. (op. cit.) describes how this information can be extracted from the business using different types of questions. As managers in the business will typically not be statistical experts, the challenge is to ask the questions in the easiest way possible, while still extracting useful information. Alderweireld, Garcia & Léonard (unpublished) discuss how to build a questionnaire that is understood by managers in the business and how to transfer the information provided in accurate capital figures. Generally for each scenario, information of the form “A loss of $x$ occurs every $d$ years” must to be collected.

6.2.4.4 The process of how scenarios will be set, who must provide the information, the controls around the scenario setting and the frequency of updating must be specified in the operational risk management framework.

6.2.4.5 The information can either be gathered by sending questionnaires to the relevant managers or by having workshops where the line manager, business unit risk
managers and modellers are all in the same room and talk through the questions. Internal loss data and external data will be provided to the participants to inform their discussion even if only a few data points are available. Consideration will also be given to the controls in the business and the effectiveness of the controls.

6.2.4.6 There are a variety of ways in which the scenario analysis can feed into the capital calculation. At the one extreme the question can be asked what loss is expected at the desired percentile (e.g. what is loss is expected in a 1-in-200-year event) and this can be used as the capital. Where internal loss data or external data are available, the results from the scenario can be combined with the data. Dutta & Babbel (unpublished) explain that care is required when combining scenario data with internal data. As an example, if a financial institution that has been collecting data for five years adds a 1-in-10-year scenario to the internal loss data they effectively change the frequency of the event to 1-in-5 years. The paper explains methods to combine the scenario data with internal loss data without introducing bias. Alternatively, frequency and severity distributions can be fitted to the scenarios and these can be used in the modelling for the category. The adjustments required to normal maximum likelihood estimators and fitting procedures to do this is described in detail in FMR (op. cit.) and forms the basis for the simulations performed in section 7.2.

6.2.4.7 Scenario analysis should be supplemented by sensitivity testing to understand how sensitive the capital is to the scenario information.

6.2.4.8 Arguably, advanced modelling using ‘fictitious’ data arising from scenarios may be considered spurious. Apart from the benefits it brings in involving line managers responsible for the operational risk in the capital calculation, it greatly enhances the understanding of the impact of different risks even though the capital numbers may be incorrect.

6.2.5 Business Environment and External Control Factors

6.2.5.1 It is not clear how this will feed into the LDA approach, but a forward looking capital calculation should take cognisance of the business environment and other external factors that may cause future experience to be different from the past. As an example Dexter et al. (op. cit.) talk specifically about possible future mis-selling or Treating Customers Fairly (TCF) issues for life insurers. At some point in the future, current existing products may be deemed to be mis-sold. Such developments should be allowed for in the modelling.

6.3 MODELLING

6.3.1 The LDA approach is described in detail in many papers. The reader is referred to Embrechts, Furrer & Kaufman (op. cit.) and FMR (op. cit.) as a starting point. Lubbe & Snyman (2010) is a practical paper describing how a South African bank applies the LDA. Tripp et al. (op. cit.) present a case study of how the method can be applied to an insurer.
6.3.2 The LDA approach involves fitting a compound distribution to the data obtained as described in the previous section. For every operational risk category a frequency distribution is fitted to the number of events occurring per year and a severity distribution is fitted to the loss amounts. This is often referred to as the actuarial approach as this is similar to the method used to model claims in non-life insurance. It is important to be aware of the main assumptions underlying this method: namely that the operational risk losses are independent and identically distributed, and are independent of the frequency distribution.

6.3.3 Typically the Poisson distribution is used as the frequency distribution, but other discrete distributions such as the Negative Binomial can also be used. A severity distribution appropriate to the features of the data and the type of risk being modelled must be chosen for each operational risk category. Apart from the requirements that the distribution must only have positive values it must also be negatively skewed to allow for potential very large operational risk losses. Dexter et al. (op. cit.) lists as possible severity distributions the Lognormal distribution, Weibull distribution, Beta distribution and Generalised Pareto Distribution. The choice of a distribution for each operational risk category will be driven by the features of the data.

6.3.4 Any statistical fitting methodology can be used to fit the distribution to the data and goodness of fit tests must be performed to ensure the fit is adequate. Lubbe & Snyman (op. cit.) emphasise the importance of exploratory data analysis and give potential graphical and statistical goodness-of-fit tests that can be used. Care needs to be taken to allow correctly for truncation in the data. FMR (op. cit.) show how the severity distribution should be fitted in the presence of truncation. The results of a simulation study presented in section 7.1 show that not allowing for truncation when fitting the distributions can lead to a significant understatement of the operational risk capital. De Fontnouvelle et al. (op. cit.) explain a method of treating the truncation point as stochastic which could be useful for external data where different, unknown truncation points may have been applied.

6.3.5 There are several issues to consider when fitting the severity distribution. Large historical operational risk losses show that the underlying distribution can be very long tailed. Most of the available data will be from the body of the distribution. If a distribution is fitted to the data without allowing for this, one is likely to understate the capital which is from the tail of the distribution. One potential solution is to fit a different distribution to the body and the tail of the distribution. For the tail distribution, Extreme Value Theory (EVT) is often used. A threshold for large losses is chosen and losses above this threshold are modelled using an appropriate distribution, usually the Generalised Pareto Distribution. Tripp et al. (op. cit.) gives a useful practical example of how this can be used by a general insurer. There is a lot of literature available dealing with EVT. The reader is referred to Chavez-Demoulin, Embrechts & Nešhová (unpublished) where this is also discussed in the context of operational risk modelling. To combine the distributions for the body and tail some type of scaling will be necessary to make sure the distributions fit smoothly and ensure that it is still a valid distribution function.
6.3.6 Often it is not possible to obtain the distribution function of a compound distribution analytically. Heckman & Meyers (1983) give an algorithm that can be used and discuss numeric methods available. However, with computing power being freely available, Monte Carlo simulation is performed to obtain the distribution function. As a first step one would simulate a large number, say 10 000, of values from the frequency distribution giving the number of events for each of the simulations. Values from the severity distribution are then simulated to give a loss size for each event and then summed for each simulation to give the total loss per simulation. This is then ordered to give the empirical distribution function.

6.3.7 A further consideration is how to allow for correlation between the different categories of operational risk. If the capital is taken as the desired percentile from the distributions fitted for each claim and the resulting capital figures are added together to give the total capital for operational risk, there is an assumption that the events captured in the different operational risk categories are perfectly correlated and will all occur at the same time. Cooper, Piwcewics & Warren (op. cit.) explain that operational risks are generally correlated due to common factors creating a level of correlation. A way to deal with the interdependence between the various categories needs to be found.

6.3.8 It is important to consider the dependence between different operational risk categories in more detail. The correlation stems from two main sources: either the frequencies can be correlated or the severities can be correlated. The first is fairly easy to motivate as often a single cause, e.g. poorly trained staff, can cause losses under different event categories; in this example, possibly under Business Disruption and Systems Failures and Execution, Delivery and Process Management. However, the second source of correlation is more problematic as it is unlikely that the severities under different categories will be correlated while the severities in a single category are assumed to be independent. An alternative is just to consider correlation between the total losses for the category, but it is important to note that this will stem from one or both of these two sources. If correlation is as a result of frequency correlation it provides a good incentive for allowing for diversification benefits between the different categories. Franchot, Roncalli & Salomon (2004) show that even if the correlation between the frequencies is 1, the correlation between the total losses will be less than 4%.

6.3.9 Correlation is often allowed for by a simple variance-covariance approach. As discussed above, there are severe constraints around data. Whereas for some operational risk categories there may be sufficient data, others may rely almost entirely on scenario analysis. This makes it difficult to accurately calculate the correlation coefficients between the different categories. A more pragmatic approach is usually followed. A very simple approach would be to set all correlations to be one of a few pre-specified levels, e.g. 0, 0.25, 0.5, 0.75 and 1. In practice negative correlation is seldom used and this will be hard to justify. Some more advanced methods may be used where scores are given to various interrelationships between departments and risks which are...
then converted to a correlation. Where questionnaires are sent out or workshops held for scenarios analysis purposes, questions can be included to determine correlations. Alternatively the correlation parameters can be set using the internal loss data or external data and statistical techniques.

6.3.10 Copulas are very flexible joint distribution functions. Unlike for example the joint normal distribution where the marginal distribution functions all have to be normally distributed, with copulas the marginal distributions can all be different and the copula function joins them together with a certain dependency structure. This feature of copulas make them very useful for modelling operational risks. There are methods available to fit copulas and marginal distribution jointly to a dataset but, given the problems with operational risk data already highlighted, this is unlikely to be a viable approach for operational risk modelling. The reader is referred to Sweeting (2011) for a comprehensive description of copula theory and different copulas.

6.3.11 Different copulas require different parameters and with insufficient data it can often be challenging to calibrate these parameters, especially when the parameters do not have an intuitive interpretation. In practice the normal or student t copulas are therefore often used as the required parameters are the correlations between the risks as per a correlation matrix. Methods as discussed above are used to calibrate the correlation matrix with the added complexity that the matrix must be positive definite. Various methods are however available to convert a matrix to be positive definite. The student t copula has an added parameter which may be more complex to set, but has the advantage that it gives more accurate correlation in the tail.

6.3.12 The combined distribution of the copula with the compound distributions as marginal is mathematically intractable and hence Monte Carlo simulation is required. The following steps are now added to the algorithm described in ¶6.3.6 as described in Lubbe & Snyman (op. cit.). The simulated marginal distribution functions for the losses from the different operational risk categories are now combined with the chosen copula. Simulate from the copula \( n \) variables between 0 and 1 with the correlation structure implied by the copula and where \( n \) is the number of operational risk categories being modelled. By using the simulated distribution function this can be converted to a loss amount for every risk. This is then added to give the total loss for that simulation. The whole process is repeated for the number of simulations. The desired percentile from the simulated distribution is then set as the capital. This must be compared to the sum of the desired percentile from the individual simulated distributions for the different operational risk categories to understand the diversification benefit allowed for in the modelling.

6.3.13 The last factor to consider is whether to allow for any diversification between operational risk and other risk categories. Under Basel this is not allowed for banks. The standard formula SCR under Solvency II and SAM assume a correlation of 1 between operational risk and the other risk categories. Under a full internal model it may be possible to allow some diversification benefit, but this will have to be justified to the regulator. A more complicated approach, which may be easier to calibrate, is to
allow for the different operational risk categories separately and find the correlation structure between them and the other risk categories.

7. SIMULATION STUDY

7.1 Importance of Allowing for Truncation

7.1.1 This section presents the results of a simulation study performed to highlight the importance of allowing for truncation when fitting the distributions to observed loss data.

7.1.2 For the simulation study it was assumed that the true underlying distribution of an operational risk category is a Poisson frequency distribution with \( \lambda = 20 \) and a lognormal severity distribution with \( \mu = 10 \) and \( \sigma = 1 \). For each simulation, losses for five years were simulated by first simulating a number of events per year from the frequency distribution and then for each event a loss amount from the severity distribution. The data was then truncated at R5,000 to represent the situation where only losses above the R5,000 threshold are recorded. As a next step the parameters of the frequency and severity distributions were fitted using standard statistical techniques not allowing for the truncation. Further simulation was performed to obtain the empirical distribution function of the fitted distribution and the 99.5th percentile was recorded as capital. The parameters of the frequency and severity distribution were also fitted allowing for the truncation and using the formulae proposed in FMR (op. cit.). Simulation was performed to obtain the empirical distribution function of the fitted distribution allowing for capital and the 99.5th percentile was recorded as capital.

7.1.3 100 simulations were performed. The frequency plot in Figure 1 shows that allowing for truncation the capital is spread around the actual capital of R1.68 million whereas the spread is around a lower value when using standard statistical techniques.

7.1.4 It can be seen that the allowance for truncation improves the estimation of the capital and that not allowing for truncation will potentially understate the capital.

7.1.5 The large variance observed in the capital figures is as a result of the small number of observations used for the fitting given that losses for only five years were simulated and the average number of losses per year from the frequency distribution is only 20.

7.2 Scenario Analysis

7.2.1. A view often raised is that it is not appropriate to base complex modelling on qualitative scenarios set by a financial institution. In this simulation exercise it was assumed that only scenario data was used as input for the LDA.

7.2.2 To overcome the problem that people involved in the scenario setting are often not statistically trained, the method described in FMR (op. cit.) namely, to produce scenarios of the form “A loss of \( x \) or higher occurs once every \( d \) years” was used. The formulae presented in this paper are also used for the fitting of the distributions.
For the purpose of the simulations it was assumed that the true underlying distribution is a Poisson frequency distribution with $\lambda = 4$ and a lognormal severity distribution with $\mu = 11$ and $\sigma = 2$. From this the true value of $x$ was calculated for four typical values of $d$, namely 1, 2, 5 and 20 years. This will not be known exactly when setting the scenario, but it is assumed that the people involved in the scenario setting have some prior knowledge or data informing them of the ranges within which the severities fall. It was further assumed that the level of certainty reduced as $d$, the average duration between the losses, increased. Two sets of simulation were performed to show how the accuracy of the capital estimate improves when there is more certainty about the severities used in the scenarios. Table 1 shows the level of uncertainty applied to each value of $x$ and the ranges around $x$, from which it is assumed $x$ will be chosen for a setting where the severity for the 20 year event is fairly uncertain and falls between 70% and 130% of the actual value. Table 2 shows the level of uncertainty and ranges around $x$ for a setting where the uncertainty is half of that assumed for the previous scenario. For each simulation, a value for each $x$ was chosen from the range corresponding to the relevant $d$ using a uniform distribution. The compound distribution was then fitted to these parameters and the capital calculated as the 99.5th percentile of the empirical distribution function simulated using these parameters.

Figure 1. Frequency plot of capital with and with allowance for truncation in fitting
Table 1 Inputs used for simulation of scenarios under setting 1

<table>
<thead>
<tr>
<th>$d$</th>
<th>$x$</th>
<th>Level of uncertainty</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>230 724.47</td>
<td>10.0%</td>
<td>207 652.02</td>
<td>253 796.92</td>
</tr>
<tr>
<td>2</td>
<td>597 613.06</td>
<td>12.5%</td>
<td>522 911.42</td>
<td>672 314.69</td>
</tr>
<tr>
<td>5</td>
<td>1 606 722.99</td>
<td>15.0%</td>
<td>1 365 714.54</td>
<td>1 847 731.44</td>
</tr>
<tr>
<td>20</td>
<td>5 297 817.26</td>
<td>30.0%</td>
<td>3 708 472.08</td>
<td>6 887 162.43</td>
</tr>
</tbody>
</table>

Table 2 Inputs used for simulation of scenarios under setting 2

<table>
<thead>
<tr>
<th>$d$</th>
<th>$x$</th>
<th>Level of uncertainty</th>
<th>Lower bound</th>
<th>Upper bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>230 724.47</td>
<td>5%</td>
<td>219 188.25</td>
<td>242 260.69</td>
</tr>
<tr>
<td>2</td>
<td>597 613.06</td>
<td>6.3%</td>
<td>560 262.24</td>
<td>634 963.87</td>
</tr>
<tr>
<td>5</td>
<td>1 606 722.99</td>
<td>7.5%</td>
<td>1 486 218.77</td>
<td>1 727 227.22</td>
</tr>
<tr>
<td>20</td>
<td>5 297 817.26</td>
<td>15.0%</td>
<td>4 503 144.67</td>
<td>6 092 489.84</td>
</tr>
</tbody>
</table>

7.2.4 The results of the simulation exercise are shown in Table 3 which gives several summary statistics of the capital figures for the 1000 simulations. This should be compared with the actual capital figure for the fitted distribution of R26.7 million. It is clear that for the level of uncertainty there is a wide variation in the capital charge and that little reliance can therefore be placed on an estimate of the capital based on a single scenario. However, increasing the certainty of the scenarios, for example by basing it on more data or analysis, will significantly improve the calculated capital. It should also be noted that the average across the 1000 simulations is very close to the actual figure suggesting that using some form of randomisation of the scenarios to allow for the uncertainty of the scenarios, combined with simulation can significantly improve the estimates.

7.2.5 The large variation in the capital charge as per Table 3 for setting 1 and the marked improvement when halving the uncertainty emphasises the importance of data. Data can be used to inform the scenarios and thereby reducing uncertainty or can be combined with scenarios using the methods described in FMR (op. cit.).

7.2.6 Until sufficient data is available in the insurance industry and with individual insurers, scenario analysis will play an important role in the modelling of operational risk. However, the simulation study show that every effort should be taken to improve the certainty around the scenarios.

8. CONCLUSION

8.1 The intention of this paper is to provide a high-level overview of the many factors that needs to be considered when modelling operational risk. It is largely based on the LDA approach used in banking. The method may require advanced statistical techniques
such as EVTs and copulas in certain circumstances. Many excellent resources are available covering these and other topics, some of which are referenced in this paper. However, the techniques employed will ultimately be determined by the exact nature of the risks modelled, the data available and other constraints. As an example of one of the features of the data determining the modelling, section 7.1 shows the importance of allowing for truncation when fitting distributions. The method employed will only work for a constant, fixed threshold and more advanced methods using stochastic thresholds are required for unknown or variable thresholds. However, the choice of method can only be made once one understands the intricacies of the data.

8.2 In terms of using data to calibrate operational risk capital models, the insurance industry lags behind the banking industry in internal data collection as well as consortium data schemes. An alternative is the use of scenarios. Section 7.2 shows that using scenarios only can lead to very imprecise estimates of capital, but that this bias can be reduced somewhat by applying randomisation. These estimates can be improved if the uncertainty in the scenarios are reduced by data, but the true value of scenarios lie in supplementing data.
8.3 Despite the number of challenges and pitfalls when attempting to model operational risk, any attempt to model operational risk has the potential to improve understanding of the risk category and ultimately help to reduce operational risk losses.

REFERENCES


