Measuring operational risk in financial institutions

Operational risk is now seen as a major risk for financial institutions. This paper considers the various methods available to measure operational risk, and identifies a new framework for analysis.

A framework to measure operational risk
The framework we propose to measure Operational Risk (OpRisk) is inspired by a statement given by the United States former Secretary of Defense, Donald Rumsfeld. Thus we have called the method the ‘Rumsfeld Approach’. We broadly categorise all OpRisk into three categories:

- Known-Known – risks that we know exist and how to model;
- Known-Unknown – risks that we know exist but do not know how to model (or are difficult to model, e.g. legal risk); and
- Unknown-Unknown – risks that we are unaware of.

The motivation behind the Rumsfeld approach is to provide a consistent framework that would take into account all three categories of OpRisk to determine the risk capital for a financial institution. The subsequent sections discuss the suitable methods available to measure the OpRisk for each category.

Modelling Known-Known OpRisk
OpRisks that we know exist and can be modelled are categorised as Known-Known OpRisk. There are many approaches that have been used by the financial industry as well as other industries to model such risk. Most of these approaches can be broadly subdivided into two categories: top-down approaches – which attempt to model aggregate operational losses without giving attention to underlying operational process – and bottom-up approaches – which attempt to model losses by mapping the operational process to predetermined risk components.
Scalars
Scalars are simplistic top-down methods to measure operational risk. The methodology assumes operational risk to be a predetermined percentage of a business scalar such as gross income, operational costs, assets, funds under management etc. (Lawrence 2000). Two well-known examples of this approach are the ‘basic indicator approach’ and the ‘standardised approach’ specified for banks under Basel II. The main advantage of using scalars is that it’s a low-cost method of measuring OpRisk. However, the main disadvantage is that the cost of capital is not directly linked to the loss data, operational process or the control process. Thus the accuracy of the model is questionable.

Regression and trend analysis
The models based on regression and trend analysis attempt to identify the key risk indicators (KRIs, e.g. audit ratings, employee turnover and transaction volume) that drive the operational risk and then use these KRIs to monitor and measure OpRisk. Since KRIs are directly linked to the operational process, the model gives the line managers a behavioural incentive to keep the KRIs at a desired level in order to manage the OpRisk.

Financial statement models
Financial statement models assume operational risk has an influence on financial results such as stock returns, earnings, expenses and profitability. The first step in the modelling process is to identify a target variable which is highly influenced by the operational risk. Then the target variable is modelled using external risk factors which drive the target variable. Operational risk is measured as the variance in the target variable that is unexplained by the external risk factors. CAPM-based models (Hoffman 2002; Ceske et al. 2000) are examples of this approach.

Due to the highly skewed nature of operational loss data, conventional frequency and severity models used in LDA are unable to provide adequate results in describing the loss data; especially in the extreme percentiles. A further shortcoming of the LDA is that it does not take into account risk diversification when calculating the capital charge. LDA is not suitable to be used when significant changes have occurred in the business or control environment.

CAPM-based models assume OpRisk is the differential between risk measured by CAPM and the risk measured separately by the credit and market risk models. The main advantage of financial statement models is that they are easy to implement and inputs are readily available. A shortcoming of this approach is that not all OpRisks are sensitive to external risk factors and it is possible that some important OpRisk such as fraud can be overlooked in such instances.

Expected loss models
Expected loss models attempt to project future expected operational losses by using the institution’s internal loss data as a key input to measuring operational risk. Thus, in contrast to scalars, the capital charge is directly linked to the institution’s loss distribution. These models assume unexpected losses (the tail of the loss distribution) can be extrapolated using expected losses (the mean of the loss distribution). A well-known example of this approach is the ‘internal measurement approach’ (IMA), one of the methods prescribed under the Basel II ‘advanced measurement approach’ (AMA). The main advantage of the expected loss model approach is that it directly links the firm’s loss experience into OpRisk capital calculations as opposed to the top-down models discussed earlier. However, the main drawback of this method is that it does not attempt to assess the tail of the loss distribution directly.

Loss distribution approach
The loss distribution approach (LDA) is a technique that has been used to model insurance losses for many years. Similar to IMA, LDA categorises the risk events in a matrix by business line and event type. But, rather than compute the expected losses, LDA estimates two separate distributions for frequency of losses and severity of losses for each risk cell using internal data.

In theory, LDA is able to provide superior results to the expected loss models since it makes full use of the internal data to directly measure the unexpected losses. However, research including Moscadelli (2004) and (Evans et al. 2007) has demonstrated that due to the highly skewed nature of operational loss data, conventional frequency and severity models used in LDA are unable to provide adequate results in describing the loss data, especially in the extreme percentiles. A further shortcoming of the LDA is that it does not take into account risk diversification when calculating the capital charge. LDA is not suitable to be used when significant changes have occurred in the business or control environment. Many improvements for the LDA approach have been proposed by various authors to address the issues. One method that has been put forward to model the tail of the distribution is to use the extreme value theory (EVT). Moscadelli (2004) used the peak-over-threshold method (POT) to model the tail of the loss distribution to provide significantly better fit to the operational loss data in the extreme percentiles. Similar results have been reported by Evans et al. (2007).
The Delta-EVT method has many advantages. The Delta method employed to quantify high-frequency events is based on the classic error propagation law which is an ISO standard for measuring uncertainty (ISO 1993), and the Delta method is fairly forward-looking as the key inputs are very sensitive to the operational exposure and the changes in the control environment.

Then assuming unit pricing and accounting methods used to value each investment method are similar, in other words assuming perfect correlation among liability valuation errors for each investment option, total error in valuation due to OpRisk is:

$$(\delta L)^2 = \left( \sum_{i=1}^{m} \delta L_i \right)^2 = \left( \sum_{i=1}^{m} \left( TU_i \right)^2 \sigma_{UP}^2 + \left( UP_i \right)^2 \sigma_{TU}^2 \right)^2$$

The Delta method only measures the operational risk that can be related to causal factors. Most of the catastrophic losses and control breakdowns are not related to causal factors. Thus King (2001) suggests the use of EVT to quantify such risk due to rare events. He proposes obtaining the maximum operating loss due to causal factors using the Delta method and setting it as a threshold to filter the large losses, and then using EVT to model the excess losses. The Delta-EVT method has many advantages. The Delta method employed to quantify high-frequency events is based on the classic error propagation law which is an ISO standard for measuring uncertainty (ISO 1993), and the Delta method is fairly forward-looking as the key inputs are very sensitive to the operational exposure and the changes in the control environment. Furthermore, even when historic data is not available, the Delta method can be employed using expert judgment to estimate standard deviations. Coupled with EVT to measure high percentile losses, a Delta-EVT method provides an elegant solution to quantify OpRisk.

**Risk drivers and control approach (RDCA)**

The RDCA approach, which is also known as scorecards, is one of the alternative methods specified by Basel II under the AMA regime (Basel 2001). This approach heavily relies on control self-assessment (CSA) techniques to identify the principal drivers and controls of OpRisk. The RDCA approach has the advantage of involving the line managers in the modelling process, and the method is more transparent to managers as risk exposures are measured using statistics they are familiar with. It is possible to compare the performance of managers by comparing the scores of the business units they are responsible for. The RDCA approach not only provides the means to quantify OpRisk but also to monitor and manage OpRisk.

**Delta-EVT**

Delta-EVT is a method developed by King (2001) to quantify OpRisk. The method measures operational risk as the uncertainty of earnings due to two types of operational losses: first, the high frequency-low severity losses that can be mapped to causal factors; and second, the low-frequency high-severity losses that cannot be mapped to causal factors (e.g. control breakdowns). King (2001) proposes modelling the low severity losses using the Delta method and extreme losses using EVT. The Delta method attempts to quantify the aggregate uncertainty in profits propagated from uncertainties in each OpRisk factors. For example, consider the simple case where liability of a superannuation fund with investment options calculated using the formula:

\[
\text{Liability (L)} = \sum_{i=1}^{m} \bar{L}_i = \sum_{i=1}^{m} \text{total number of units} \times \left( TU_i \right) \times \text{unit price} \quad (3.7)
\]

According to this formula an operational loss due to mispricing of liability can happen due to two reasons: a unit pricing error or an accounting error in the total number of units. Thus taking unit pricing errors and accounting errors as the risk factors, we can write the formula for volatility of liability due to OpRisk in ith investment using the delta method as follows:

\[
(\delta L_i)^2 = \left( \frac{\partial L_i}{\partial UP} \right)^2 (\delta UP)^2 + \left( \frac{\partial L_i}{\partial TU} \right)^2 (\delta TU)^2
\]

\[
= (TU_i)^2 (\delta UP)^2 + (UP_i)^2 (\delta TU)^2
\]

\[
= (TU_i)^2 \sigma_{UP}^2 + (UP_i)^2 \sigma_{TU}^2
\]

The prefix represents the error term.
Causal models – Bayesian belief networks (BBN)
Bayesian belief networks are a type of causal model which employ Bayesian probability theory to model cause and effect in a system. In contrast to a Delta-EVT method, BBNs allow us to model events where casual events exist but deterministic relationships cannot be obtained (Mast et al. 1999). Applications of BBNs can be found in the nuclear industry (Santoso et al. 1999), medical diagnosis (Nikovski 2000), data mining (Heckerman 1997), intelligent trouble shooting systems (Heckerman & Breese 1996), and aviation failure diagnosis (Mast et al. 1999).

A BBN is a set of variables called nodes which are connected by arrows (known as directed edges, or arcs) representing the dependencies among the nodes such that there are no directed cycles. Once the BBN has been built it can be used to measure, monitor and manage OpRisk. An advantage of using a BBN to model OpRisk is that it allows management to dynamically observe the changes to the loss distribution with respect to changes in the business and control environment.

Other models using a process approach
There are many other models based on the principles of process approach. Some of them include reliability models, connectivity models, system dynamics, and neural networks. Reliability models have been in use for many years in engineering to measure and mitigate OpRisk in power plants, nuclear reactors etc. They model the time between OpRisk events rather than their frequency (Saunders et al. 2004). Thus these models may become useful in measuring particular operational risk (e.g. IT failure) at a business unit level. A system dynamics approach is another causal model that has been proposed to measure OpRisk. A discussion contributed by Jerry Miccolis and Samir Shah of the use of a system dynamics approach at Tillinghast/Tower Perrin can be found in Hoffman (2002). Another promising method in the development stage is neural networks. Perera (2000) claims that the neural networks developed at NASA to analyse reliability of micro-electromechanical systems (MEMS) can be adapted to measure operational risk for financial institutions.

So which method to choose?
As discussed above, there are many methods available to model Known-Known OpRisk. The method chosen will depend on factors such as data availability, time and budget constraints. Top-down methods such as scalars, financial statement models and trend analysis are suitable for small institutions that do not have the capability to carry out sophisticated modelling. On the other hand, large institutions may find bottom-up methods such as LDA and causal modelling more attractive as they will allow the firm to gain a better understanding of its OpRisk. Among the bottom-up methods available, causal models provide superior results in terms of accuracy, forward-looking capital estimates, behavioural impact and early warning signals. Use of KRI in the RDCA approach makes RDCA somewhat forward looking. If properly set up, RDCA can provide valuable information to OpRisk managers on how to manage risk and even establish early warning signals. Causal models could be quite useful to measure particularly high risk OpRisk at business unit level. For example, given that most of the large-scale losses in recent years, such as Sumitomo, Barings, Allied Irish, Lehman, and IAG, were infrequent and, due to different causes, the time and cost involved in building a causal model may not be unreasonable to measure and monitor such OpRisk.

Assessing Known-Unknown OpRisk
In order to model risk that we know exists but cannot model (e.g. legal risk), we propose a methodology based on the Solvency II loss-given-default approach. Under Solvency II, European insurers need to stress test the survivability of the business assuming large catastrophic industry losses. This method is called the loss-given-default approach. The method simply looks at whether an insurer has enough capital to cover their exposures under a given set of catastrophic industry losses (e.g. European windstorm causing a $4 billion industry loss). The method makes no attempt to quantify the frequency of losses. The Black Swan approach outlined below is a slightly modified version of the loss-given-default approach such that it would be suitable to measure OpRisk. The basic steps of the Black Swan approach are as follows:

- Identify the types of OpRisk classes that we cannot model using conventional models.
- Obtain industry loss data for each risk class and make corrections for inherent bias.
- Use the adjusted data to find the maximum operational loss experienced by similar organisations in the industry under each OpRisk class.
- Survivability of the business is stress tested against the maximum loss. If the business cannot survive, then the necessary capital or risk management practice is put forward for adoption.

Correcting for inherent bias
The most important step in the Black Swan approach is to correct for inherent bias in the data since data that has not been corrected for bias can yield perverse capital estimates. According to APRA (2007) there are mainly three types of bias which affect external data:

- Reporting bias – occurs when a different threshold has been used by institutions to report losses.
- Control bias – occurs when data is collected from institutions with different control systems.
- Scale bias – occurs when data is collected from institutions with different sizes.

The main advantage of the Black Swan approach is that it is simple to implement and the inputs are readily available. Unlike most of the methods discussed earlier, the Black Swan approach focuses on risks that pose the greatest threat to the solvency of the business.
Among the bottom-up methods available, causal models provide superior results in terms of accuracy, forward-looking capital estimates, behavioural impact and early warning signals.

Risk margin for Unknown-Unknown OpRisk
Unknown-Unknown OpRisk is the OpRisk that the firm is exposed to but is unaware of. The only sensible way to account for these types of risk is to add a risk margin above the capital charge calculated under Known-Known and Known-Unknown OpRisk. Benchmarking is one of the easiest ways to determine the appropriate risk margin. This method simply looks at the OpRisk capital held by similar firms in the industry to manage their unknown-unknown risk and benchmark against it. This is a proxy measure rather than a real quantification, so it is necessary to use expert judgment when benchmarking against each other so that the nature of the firm’s business environment and control process is taken into account when deciding the risk margin.

Conclusion
In this paper we have introduced a consistent framework to measure operational risk such that all three categories of risk: known-known, known-unknown and unknown-unknown risks are taken into account when determining the capital charge. There are many methods available to measure known-known risks. Choice of the method will depend on the factors such as data availability, and time and budget constraints. Most of the top-down models available to measure Known-Known risks are easy to implement, low cost and suitable when in need of quick answers. However, the accuracy of these models is questionable. On the other hand, bottom-up approaches are able to provide more accurate capital estimates as they make full use of the internal loss data and, in some cases, even external data and expert opinion.

Causal models such as Bayesian networks seem to most likely provide best results in terms of accuracy but, due to the time and costs involved in setting up a causal model, most businesses might find these models less feasible to implement. The RDCA method seems to provide a good trade-off between performance and time/cost. If properly set up, an RDCA model can provide fairly forward-looking estimates of OpRisk capital charge, behavioural incentives and early warning signals to managers.

In order to assess Known-Unknown OpRisk we propose stress testing using the Black Swan approach, which is a modified version of the loss-given-default approach. Unknown-Unknown risk is taken into account by adding a risk margin above the capital estimates obtained under known-known risk and known-unknown risk.

Note
1 Methods recommended under Basel II advanced measurement approach include: Internal Measurement Approach (IMA), Scenario Based Advanced Measurement Approach (shAMA), Risk Drivers and Controls Approach (RDCA) and Loss Distribution Approach (LDA).

References