Methods to Measure Operational Risk in the Superannuation Industry

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Abstract:

Australian Government Treasury (2001a) recognizes operational risk (OpRisk) as the most significant risk for superannuation funds. Given the size of the super industry and the role it plays in the community it is of utmost importance that super fund managers take relevant actions to measure and mange their OpRisks. However measuring OpRisk is a difficult task for reasons such difficulty in identifying risk, nature of certain OpRisk (e.g. rogue traders), scarcity of data, budget and time constraints etc. The focus of this article is to explore ways in which OpRisk can be measured in practice while overcoming these difficulties. I discuss simple top-down approaches such as scalars, benchmarks, Black swan approach, Regression and trend analysis, financial statement models and more advanced bottom-up approaches such as Expected loss models, LDA, Secnario-based models and Process approaches. Article provides brief explanations on how to implement each of these methods and then discuss the advantages and disadvantages of each method and suitability of them to overcome the aforementioned difficulties of measuring OpRisk.

1. Introduction

Superannuation industry is the second largest sector in the financial services industry in Australia in terms of assets under management (Reserve Bank of Australia, 2007). APRA (2007a) reports, as of September 2007 super funds held A$1.2 trillion in assets. To most households their superannuation savings represent the most important asset after home ownership (The Australian Government Treasury, 2001a). The magnitude of the industry it self and the role it plays in the community makes the superannuation industry one of the most important sectors in the financial services industry. Though most super funds do not provide explicit guarantees on retirement benefits for their members, fact that many Australians depend on the system as their main source of retirement income makes it necessary that super funds are regulated properly to minimize the probability of failure.

Australian Government Treasury (2001a) recognizes operational risk as the most significant risk for a super fund given that market risk and investment risk is borne by the fund members. However, surprisingly there are only limited regulatory requirements for super funds to manage their operational risk compared to other industries like banking and insurance. For example, current regulatory capital requirement for super funds require approved trustees to hold only A$5 mill assets regardless of the fund size or operational process. And for those funds that operate without an approved trustee, there is no capital requirement. There have been recent government discussions to reform the prudential capital requirement for super funds in order to align the capital requirement with fund size and the operational process (Treasury, 2001b). Thus it’s highly likely that in near future superannuation industry may need to quantify their operational risk in order set up prudential capital.

This paper aims to introduce a consistent framework to measure OpRisk for the superannuation industry. In the preceding section we introduce a basic framework to measure OpRiks by categorizing OpRisk into three categories: known-known risk, known-unknown risk and unknown-unknown risk. In section 3, 4 and 5 we discuss different methodologies available to measure each risk category by looking at techniques used by different industries such as Banking, Insurance, Nuclear, Chemical and Aviation to measure their OpRisk. Here we discuss pros and cons of each methodology and possibility of extending them to measure OpRisk in the superannuation funds. Section 6 concludes.

2. A Framework to Measure Operational Risk

The framework we propose to measure OpRisk is inspired by a statement given by the United States former secretary of defense, Donald Rumsfeld. Thus we called the method *Rumsfeld Approach.* We broadly categorize all OpRisk into three categories

- Known-Known – Risk that we know exist and know how to model
- Known-Unknown – risk that we know exist but do not know how to model (or hard to model) (e.g. legal risk)
- Unknown-Unknown – risk 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. The subsequent sections discuss the suitable methods available to measure the OpRisk for each category.

3. Modeling Known-Known OpRisk

OpRisk that we know exist and can be modeled are categorized as known-known OpRisk. There are many approaches that have been used by the financial industry as well in 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 at each risk cell by mapping the operational process to risk cells and then aggregate them across.

3.1 Top-Down Models

3.1.1 Scalars

Scalars are simplistic top-down methods to measure operational risk. Approach assumes operational risk to be a pre-determined 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 “standardized approach” specified for banks under Basel II.

1) Basic indicator approach

The basic indicator approach is the simplest method recommended by the Basel II committee to measure operational risk for banks. Banks using this approach need to hold operational risk capital equal to the average positive annual gross income over the previous three years scaled by a fixed percentage set by the regulator. Formula to calculate the OpRisk capital charge under basic indicator approach is given in (3.1), where GI_i^+ is the positive annual gross income for the i^{th} year and α is the fixed scalar, set by the regulator. Currently α is taken as 15 per cent.

$$\text{Capital Charge} = \frac{\sum_{i=1}^{3} \alpha \times GI_i^+}{3} \qquad \Leftarrow (3.1)$$

2) Standardized approach

Standardize approach for banks under Basel II require them to map their gross income into eight business lines; corporate finance, trading and sales, retail banking, commercial banking, payment and settlement, agency services, asset management, and retail brokerage. Capital charge is then calculated by scaling the annual gross income for each business line by a fixed percentage specified by the regulator and aggregating them across. Formula for calculating the capital charge is given in (3.2)

$$\text{Capital Charge} = \frac{\sum_{j=1}^{3} \max\left[\sum_{i=1}^{3}\left(\beta_i \times GI_{i,j}\right), 0\right]}{3} \qquad \Leftarrow (3.2)$$

where,

$GI_{i,j}$ is the gross income for the i^{th} year on j^{th} business line. β_i is the scalar, set by the regulator for each of the business area. Currently values for β_i range from 12 per cent to 18 per cent depending on the risk inherent in the business line.

Both basic indicator approach and the standardized used by banks can be easily implemented in a super fund by either taking gross income or funds under management as the business scalar for equations (3.1) and (3.2). Main advantage of scalars is that it’s a low cost method to measure OpRisk. However the main disadvantage is that the capital charge is not directly linked to the loss data, operational process or the control process. Thus the accuracy of the model is questionable. Furthermore model does not provide any information on the types of operational risk events, their risk profiles and how to control them. In addition these models do not attempt to quantify the low frequency-high severity (LF/HS) events which impose the highest threat to the solvency of the firm.

3.1.3 Regression and Trend Analysis

The models based on regression and trend analysis attempt to identify the key risk indicators (KRI) (e.g. audit ratings, employee turnover, transaction volume etc.) that drives the operational risk and then use these KRI to monitor and measure OpRisk. The objective is to obtain a function of the form (3.3) and estimate constants α and β_i by regressing against historic losses.

$$\text{Operational loss} = \alpha + \sum \beta_i f(KRI_i) \qquad \Leftarrow (3.3)$$

There are several benefits in use of KRIs as an input to measure OpRisk. Since KRI are directly linked to the operational process, model gives the line mangers behavioral incentive to keep the KRIs at a desired level in order to manage the OpRisk. Furthermore, changes in the control environment are usually reflected much quickly in the KRIs making the output of the model forward-looking compared to other types of models that solely depend on historic data. Therefore these types of models can be useful to monitor OpRisk and provide early warning signals to the management.

A main drawback of the models based on regression and trend analysis is the difficulty in finding a function of the form (3.3) that would clearly explain the relationship between operational losses and KRIs. Furthermore, these types of models are not efficient in measuring LF/HS risk as regression techniques require large amount of data. Therefore they are more appropriate to use at a business unit level to monitor/manage high frequency operational risk or use as a technique to allocate risk capital among business units that has been determined by other means (Ceske et al., 2000).

2.1.4 Financial Statement Models

Financial statement models assume operational risk has an influence on the financial data such as stock returns, earnings, expenses, profitability etc. First step in the modeling process is to identify a target variable which is highly influenced by the operational risk. Then the target variable is modeled 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.

An example of this approach is **CAPM-based models** (Hoffman, 2002, Ceske et al., 2000). 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.

Another example of this approach is the **Multi-factor stock return model** (Saunders et al., 2004). This model specifies the stock return can be modeled using a similar formula as in (3.4)

$$R = \alpha + \sum \beta_i f(I_i) + \varepsilon \qquad \Leftarrow (3.4)$$

where, R is the stock return, $f(I_i)$ are functions of the external risk factors I_i such as ASX200, CPI etc, α , β_i are constants and ε is the residual term. Operational risk is measured as the variance of the residual term (σ_ε^2**).** More examples of financial statement models can be found in Saunders et al. (2004) and Ceske (2000).

The main advantage of financial statement models is that they are easy to implement and inputs are readily available. They look at the firm-wide view, thus suitable for determining the total OpRisk capital charge for a firm. However due to their firm-wide view they cannot be employed to determine the OpRisk capital allocation among business units. Another short coming of this approach is that not all OpRisk are sensitive for external risk factors. It is possible that some important OpRisk such as fraud can be overlooked in such instances. Another drawback of the method is that they are inefficient in measuring LF/HS risk events since model do not perform well when continuity of the financial data has been disrupted by a large scale event such as catastrophic loss, mergers and acquisitions etc. (Saunders et al., 2004).

3.2 Bottom-Up Models

3.2.1 Expected Loss Models

Expected loss models attempt to project future expected operational losses by using institution's internal loss data as a key input to measure operational risk. Thus in contrast to scalars and benchmarks, 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 Basel II "advanced measurement approach"(AMA)[1]. Key steps in IMA can be identified as follows

1) Identify the key risk events in a firm and categorize them on a matrix by business line and event type.
2) Expected loss (EL) for each risk cell in the matrix is calculated using firm's internal data.
3) Extrapolate the unexpected losses (UL) using EL. To achieve this IMA assumes there is a linear relationship between UL and EL and the ratio between UL and EL is taken as gamma (γ). Gamma is estimated by developing an industry wide operational loss distribution and taking the ratio of industry EL to a high percentile of the industry loss distribution, say 99%. (see fig 3.1). The product of EL for each risk cell and gamma will give the maximum amount of loss per holding period.

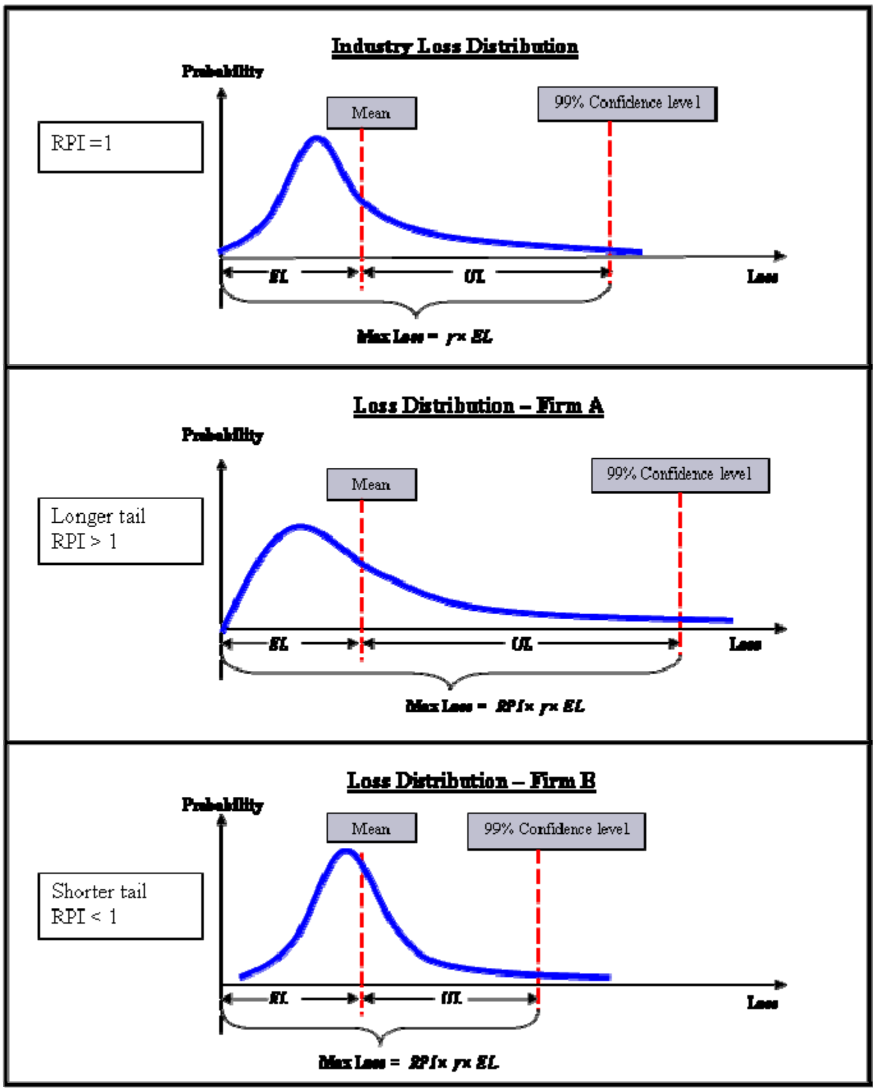
However the gamma for each firm will be different due to reasons such as operational process, business & control environment, etc. For example firms with weak OpRisk control process will tend to have a long tail operational loss distribution. Thus their gamma would be greater than

[1] Methods recommended under Basel II advanced measurement approach includes: Internal Measurement Approach (IMA), Scenario Based Advanced Measurement Approach (sbAMA), Risk Drivers and Controls Approach (RDCA) and Loss Distribution Approach (LDA)

the industry gamma. Converse will be true for firms with good OpRisk management. In order to account for the difference in the shape between firm's loss distribution and industry's loss distributions, the product of EL and gamma is multiplied by a risk profile index (RPI) (see fig 3.1). Formula to calculate the OpRisk charge for IMA is given in (3.5), where (*i*,*j*) combination represent each risk cell.

$$\text{Capital Charge} = \sum_{\text{all } j} \sum_{\text{all } i} \left(\gamma_{i,j} \times \text{RPI}_{i,j} \times EL_{i,j} \right) \qquad \Leftarrow (3.5)$$

Figure 3.1: Estimation of Gamma and RPI



Source: Mori & Harada (2001)

It should be noted that the IMA does not take into account the risk diversification between risk cells. IMA simply aggregate the capital charges for each risk cell to obtain the total capital charge for the firm. It is possible to develop an expected loss model which takes into account the risk diversification. However accounting for correlations between the risk cells is quite difficult, especially when there isn't enough data.

The main advantage of the expected loss model approach is that it directly links the firm's loss experience into OpRisk capital calculations oppose to the top-down models discussed earlier. Furthermore method is not as data intensive as compared to other models that use historical loss data such as LDA (discussed below). In absence of sufficient historic data for particular risk cell it is possible to make subjective estimates of the EL using expert opinion.

However, the main drawback of this method is that they do not attempt to assess the tail of the loss distribution directly. Assumption of a stable relationship between unexpected losses and the expected losses need to be tested more thoroughly before it is being used. In addition model is backward-looking as it solely depends on the historic data to model OpRisk. History does not necessarily have to reflect the future; especially when there have been considerable changes in the business and control processes. However this issue can be easily overcome by adjusting the estimated EL using expert opinion to reflect the changes in the business and control environment. Another criticism of the method is that it does not provide much information regarding how to manage OpRisk since capital charge estimation procedure is not directly linked to the business and control process.

3.2.2 Loss Distribution Approach (Actuarial Approach)

Loss distribution approach (LDA) is a borrowed technique from actuarial industry which has being used to model insurance losses for many years. Similar to IMA, LDA categorize the risk events on a matrix by business line and event type. But rather than compute the expected losses, LDA estimates two separates distributions for frequency of losses and severity of losses for each risk cell using internal data. Then using the model given in (3.6), where L_i is the loss for a given risk cell, N is the number of losses (frequency) and X_k is the severity of losses, frequency and severity distributions are combined using convolution technique such as Monte-Carlo simulation to obtain a total loss distribution over a holding period

$$L_i = \sum_{k=1}^{N} X_k \qquad \Leftarrow (3.6)$$

Then VaR for each risk cell is calculated and they are aggregated across to obtain the capital charge.

$$\text{Capital Charge} = \sum_i \sum_j VaR_{ij}(\alpha)$$

In theory LDA is able to provide superior results than the expected loss models described earlier since it makes full use of the internal data to directly measure the unexpected losses. However many research including Moscadelli (2004), (Evans et al., 2007) have demonstrated that due to highly skewed nature of operational loss data, conventional frequency and severity models used in LDA are unable provide adequate results in describing the loss data; especially in the extreme percentiles. A further short coming of the LDA is that it does not take into account risk diversification when calculating the capital charge. One can argue that most OpRisk categories are not correlated thus adding up capital charges for each risk cell to obtain the total capital charge is highly conservative. Another issue with the LDA is the intense need for data. In practice it is difficult to find adequate internal loss data for each business line and event type combination. A further criticism of LDA is that it is backward-looking as method relies on historic data as the primary input. Thus LDA is not suitable to be used at instances when significant changes have occurred in the business or control environment. In addition LDA is not directly linked to the business process or the control environment thus behavioral incentive provided by LDA is fairly limited.

3.2.2.1 Improvements to LDA

Many improvements for the LDA approach have been proposed by various authors to address the aforementioned 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) demonstrates using peak-over-threshold method (POT) to model the tail of the loss distribution provides significantly better fit to the operational loss data in the extreme percentiles. Similar results have been reported by Evans et al (2007). Further discussion of the use of EVT model for extreme OpRisk losses can be found in Embrechts et al (2004), Chavez-Demoulin et al (2006) and Chavez-Demoulin & Embrechts (2004).

Though EVT provides a method to model extreme losses, scarcity of data makes it difficult to estimate the parameters of the model with sufficient confidence level. Basel II recommends combining industry data and expert opinion in order to supplement scarce internal data. Wüthrich et al (2007) propose an elegant solution to combine different data sources by using Bayesian inference. They estimate the prior distribution for frequency and severity by using industry data and then prior distributions are weighted by the actual observations and expert opinion to obtain the posterior distributions. These posterior distributions are then convoluted to obtain the aggregate loss distribution.

3.2.3 Process Approach

Models based on the process approach focus on the actual operational process of the firm to identify and measure risk, thereby providing behavioral incentive for better risk management. There are many different types of models that can be classified under process approach. Some of them include:

(i) Risk Drivers and Control Approach (RDCA)

RDCA approach which is also known as scorecards is one of the alternative methods specified by Basel II under AMA regime (Basel, 2001). This approach heavily relies on control self assessment (CSA) techniques to identify the principal drivers and controls of OpRisk. Following is the outline of the basic steps of the RDCA approach.

1) *Collecting raw data:* Managers are given questionnaires which consist of series of weighted, risk-based questions. These questions are design to collect information on organization's unique risk drivers, controls and managers' expert opinion. Answers given by the managers are then analyzed to identify the statistics that are most relevant in explaining the risk exposure of the business process.

2) *Building KRIs:* Second step is to build KRIs using the raw data that would properly reflect the OpRisk in the organization or the business unit. Building meaningful KRIs is a challenge as we would like to keep the number of KRIs that we have to monitor as little as possible in order to minimize the complexity of the model. This requires taking into account the correlation between statistics when designing the KRIs. Also we would want our KRIs to be forward looking so they could serve as an early warning system. Furthermore, KRIs should be easy to measure and monitor. More on how to design KRI can be found in Scandizzo (2005).

3) *Designing scorecards:* scorecard is a firm’s self-assessment of risk event. Scorecard would typically contain the definition of the risk event, likelihood of event, impact if event occurs, types of controls, etc. A score is given to each scorecard card by taking appropriate weights of the KRIs. Weights are usually decided by regression analysis of historic data. In the absence of past data, one may use expert opinion and validate the weights once the data become available. Once the scorecards are created, they can be used as a monitoring tool for OpRisk and evaluation tool for new control measure.

4) *Determining capital charge:* scorecards can be used to determine the capital charge by simulating risks and controls. Blunden (2003) describes three possibilities for such simulations; i) simulate the controls first and if controls fails, then simulate the risk; ii) simulate the risk first and, if a risk happens, then simulate the controls; iii) simulate both risk and controls together. Blunden (2003) states that which method to choose will depend on the data availability, efficiency of simulation, capability of the technology etc.

The RDCA approach has the advantage of involving the line managers in the modeling process. Method is more transparent to managers as risk exposures are measured using statistics they are familiar with whereby providing behavioral incentives at the front line. It is possible to compare the performance of managers by comparing the scores of the business units they are responsible for. Management practice of the unit with the best scores can be adopted by other managers prompting best practice within the organization.

Another advantage of the RDCA approach is the model output is more forward-looking compared to methods primarily rely on historic data. An undesired level of score can serve as a red flag that sends escalation warning to the senior management. Thus RDCA approach not only provides means to quantify OpRisk but also to monitor and manage OpRisk. Some OpRisk experts believe if NAB had an OpRisk management system which uses KRIs they could have avoided the A$360 million operational loss experienced in the early 2004 (Adusei-Poku, 2005).

However it should be noted that badly designed scorecards or wrong expert opinion can provide terribly wrong predictions. Mark Lawrence (2000) at ANZ Bank states *"Relying completely on scorecards could be compared to driving without looking in the rear-view mirror"*. Thus it is necessary to validate the model using historic data. Anders & Brink (2004) propose four techniques to validate the model outputs. They are

a) Organizational information: Quality of inputs is ensured by evaluating expert opinion by a third person or internal audit. Independent oversight will ensure consistency across building questionnaires, workshops procedure etc.
b) Financial information: A comparison of the sum of estimated OpRisk cost for each scenario with the past operational costs recorded in the financial accounts can validate the model output.
c) Key risk indicators: assesses whether past development of KRI are consistent with the scenario assessments.
d) Psychometric analysis: use psychometric tools to analyze the quality of data collection methods.

A major drawback of the RDCA approach is that it cannot be used efficiently in quantifying LF/HS OpRisk. As discussed earlier, key inputs of the RDCA is obtained from managers through questionnaires, workshops etc. Usually managers have little or no experience in LF/HS events and therefore are unable to provide good enough estimates of such events. Thus it's necessary take into account LF/HS events by other means such as scenario analysis.

(ii) Delta-EVT

Delta-EVT is a method developed by King (2001) to quantify OpRisk. Method measures operational risk as the uncertainty in earnings due to two types of Operational losses. First are the high probability-low severity losses that can be mapped to causal factors. The second are the rare extreme losses that cannot be mapped to causal factors (e.g. control breakdowns). King (2001) proposes to model the low severity losses using Delta method and extreme losses using EVT.

The Delta method is a technique which is based on the law of error propagation; a theory well known to anyone who has taken a Physics or Chemistry lab course in their undergraduate years. 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 *m* investment options calculated using the formula (3.7)

$$\text{Liability (L)} = \sum_{i=1}^{m} L_i = \sum_{i=1}^{m} \text{total number of units}_i \left(\text{TU}\right) \times \text{unit price}_i \left(\text{UP}\right) \qquad \Leftarrow (3.7)$$

According to formula (3.7) 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 i^{th} investment using the delta method as following

$$\begin{aligned}\left(\delta \text{L}_i\right)^2 &= \left(\frac{\partial \text{L}_i}{\partial \text{UP}_i}\right)^2 \left(\delta \text{UP}_i\right)^2 + \left(\frac{\partial \text{L}_i}{\partial \text{TU}_i}\right)^2 \left(\delta \text{TU}_i\right)^2 \\ &= \left(\text{TU}_i\right)^2 \left(\delta \text{UP}_i\right)^2 + \left(\text{UP}_i\right)^2 \left(\delta \text{TU}_i\right)^2 \\ &= \left(\text{TU}_i\right)^2 \sigma_{UP_i}^2 + \left(\text{UP}_i\right)^2 \sigma_{TU_i}^2\end{aligned}$$

δ prefix represent the error term

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

$$
\begin{aligned}
(\delta \mathrm{L})^2 &= \left(\sum_{i=1}^{m} \delta \mathrm{L}_i \right)^2 \\
&= \left(\sum_{i=1}^{m} (\mathrm{TU}_i)^2 \, \sigma_{UP_i}^2 + \ (\mathrm{UP}_i)^2 \, \sigma_{TU_i}^2 \right)^2
\end{aligned}
$$

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) suggest the use of EVT to quantify such risk due to rare events. He proposes to obtain the maximum operating loss due to causal factors using Delta method and set it as a threshold to filter the large losses. Then use EVT to model the excess losses.

Delta-EVT method has many advantages. 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). Delta method is fairly forward-looking as key inputs – uncertainties of the risk factors – are very much sensitive for the operational exposure and the changes in the control environment. For instance, in the above example any changes in the valuation models used for the purpose of unit pricing is reflected straightaway from $\sigma_{UP_i}^2$. Furthermore, even when historic data is not available Delta method can be employed using expert judgment to estimate standard deviations. Coupled with EVT to measure high percentile losses Delta-EVT method provides and elegant solution to quantify OpRisk.

However there are few drawbacks in the methodology as well. Firstly not all operational losses can be explained using deterministic functions (e.g. fraud). Furthermore, delta method assumes uncertainties associated with risk factors have normal distributions and they are small enough so that the propagated errors can be estimated using first order approximation. Another issue is the difficulty in identifying all the relevant risk factors and modeling their interactions. Thus it’s necessary to verify the loss distributions with the past experience whenever possible.

(iii) 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 Detla-EVT method described earlier where OpRisk events are modeled using list of deterministic relationships, 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 Nuclear industry (Santoso et al., 1999), medical diagnosis (Nikovski, 2000), data mining (Heckerman, 1997), intelligent trouble shooting systems (Nikovski, 2000, 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 (a.k.a. directed edges, or arcs) representing the dependencies among the nodes such that there are no directed cycles. In other words BBNs are *Directed Acyclic Graphs* (DAGs). First step in designing a BBN is to identify the variables that impact the operational losses and connect them according to dependencies. For example consider the simple BBN network given in figure 2 which models the losses due to erroneous benefit payments in a superannuation fund. Model assumes total losses due to erroneous benefit payments depend on the number of erroneous payments and the exposure which is measured by the median benefit size. Furthermore, number of erroneous benefit payments is depended on the number of benefits paid (volume) and the level of training of the staff who handles the benefit payments.

Once the BBN has been setup next step would be to estimate the conditional probability distributions for each state of the nodes such that each node A in the BBN with parents $P_1, P_2, ..., P_n$ has a probability table $\Pr(A \mid P_1, P_2, ..., P_n)$ attached to them. Usually BBN is parameterized before operational data is observed thus probabilities for each node is estimated by subjective opinion. As the data become available it is possible to update the network in order to reflect the new experience. There are many algorithms to update a BBN given new information is available for a set of nodes. As cited in Adusei-Poku (2005) some of them include; *poly-tree* algorithm (Pearl, 1988), the *clique-tree* (Lauritzen & Spiegelhalter, 1988) and *junction-tree* algorithms (Cowell et al., 1999).

Once the BBN has been built it can be used to measure, monitor and manage OpRisk. For instance in the example given in figure 2 we find the expected loss from erroneous benefit payments is $\left(50k \times 0.8506 + 200k \times 0.1281 + 400k \times 0.021 + 750k \times 0.0003\right) = 76765.35$.

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. In the given example if the management decided to give all the staff a level 2 training then the expected loss will reduce down to 75308.25. Ability to simulate the impact of managerial decisions allows management to carry out cost-benefit analysis to asses their strategies. This type of analysis can also be used for stress testing. However the main disadvantage of BBNs is the complexity involved in designing such a model. Many firms would find there isn't simply enough time and money available to build a BBN in an enterprise-wide basis. Thus it's more feasible to use BBNs to quantify and mange operational risk in particular business units with large OpRisk.

Figure 2: Simple BBN for Losses Due To Erroneous Benefit Payments

Staff Training	
Level 1	0.3
Level 2	0.7

Volume - No of Benefits Paid	
Low	0.3
Medium	0.5
High	0.2

Number of Erroneous Benefit Payments							
Training	Level 1			Level 2			Marginal Probability
Volume	Low	Med	High	Low	Med	High	
Low	0.8	0.70	0.6	0.9	0.85	0.70	0.80
Medium	0.2	0.25	0.3	0.1	0.15	0.25	0.18
High	0	0.05	0.1	0	0	0.05	0.02

Exposure ($) – Median Benefit	
<50k	0.80
50k – 100k	0.15
>100k	0.05

Yearly Loss due to Erroneous Benefit Payment										
Delay	Low			Medium			High			Marginal Prob.
Exposure ($)	<50k	50k – 100k	>100k	<50k	50k – 100k	>100k	<50k	50k – 100k	>100k	
<100k	0.9	0.80	0.70	0.80	0.70	0.60	0.60	0.50	0.35	0.8506
100k – 300k	0.1	0.15	0.24	0.15	0.25	0.30	0.25	0.30	0.40	0.1281
300k – 500k	0	0.05	0.06	0.05	0.05	0.08	0.15	0.18	0.20	0.0210
500k -1mill	0	0	0	0	0	0.02	0	0.02	0.05	0.0003

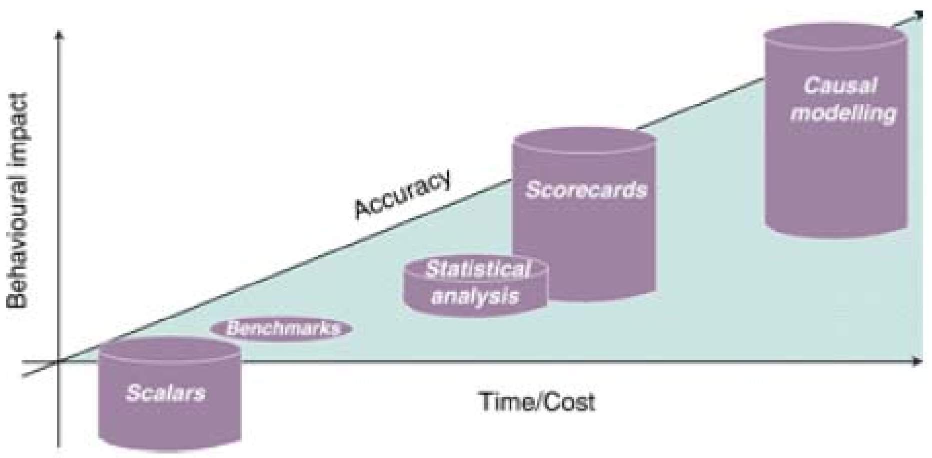
(iv) Other Models using Process Approach

There are many other models based on the principals 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 business unit level oppose to organizational level. System dynamics approach is another casual model that has been proposed to measure OpRisk. A discussion contributed by Jerry Miccolis and Samir Shah of the use of system dynamic approach at Tillinghast/ Tower Perrin can be found in Hoffman (2002). Another promising method in the development stage is the neural networks. Perera (2000) claims that the neural networks developed at NASA to analyze reliability of micro-electromechanical systems (MEMS) can be adapted to measure operational risk for financial institutions. Due to complexity of these models it is highly unlikely they will become popular in the near future. However they will at least be useful to model particular complex operational risk at business units.

3.3 So which method to choose?

As discussed above there many methods available to model known-known OpRisk. Which method to choose will depend on the factors such as problem in hand, data availability, time and budget constraints, etc. Top-down methods such as scalars, financial statement models and trend analysis is suitable for small super funds that do not have the capability to carry out sophisticated modeling. On the other hand large firms may find bottom-up methods such as LDA, casual modeling more attractive as they will allow the firm to gain better understanding of firm's OpRisk. Among the bottom-up methods available, causal models provides superior results in terms of accuracy, forward looking capital estimates, behavioral impact and early warning signals. However time and cost involve in setting up such a model can be quite significant. Attractive alternative for casual modeling is the RDCA (scorecards). Use of KRI in the RDCA approach makes RDCA some what forward looking. If properly set up, RDCA can provide valuable information to OpRisk managers on how to manage risk and even early warning signals. According to Dr. Mark Lawrence, the chief risk officer at ANZ bank of Australia, after considering many different methods to model OpRisk in the bank, ANZ finally settle down to using RDCA rather than causal models due to budget and time constraints(Lawrence, 2000). Figure 3 illustrate how ANZ ranked the different techniques in terms of time/cost, accuracy and behavioral impact. Though casual models are too costly to implement at organizational level, one should not rule them out completely. Causal models could be quite useful to measure particular high risk OpRisk at business unit level. For example, given most of the recent large scale losses such as Sumitomo, Baring, Allied Irish, NAB etc. were due to fraudulent trading activities, time and cost involve in building a causal model may not be unreasonable to measure and monitor such OpRisk.

Figure 3: ANZ Ranking of Different OpRisk Measurement Methods in Terms of Time/Cost, Accuracy and Behavioral Impact



Source: Lawrence (2000)

4. Assessing Known-Unknown OpRisk

In order to model risk that we know exist but cannot model (e.g. legal risk) we propose a methodology based on the solvency II loss-given-default approach which we call *Black Swan* approach.

Under Solvency II European insurers need to stress test the survivability of the firm under large catastrophic industry losses. This method is called the loss-given-default approach. The method simply looks at whether insurer has enough capital to cover their exposures under a given set of catastrophic industry losses (e.g. European windstorm causing $4bill industry loss). 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 will be suitable to measure OpRisk. The basic steps of the Black Swan approach are as follows

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

4.1 Correcting for Inherent Bias

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 (2007b) there are mainly three types of bias which external data is affected from

i) Reporting bias – occurs when different threshold has been used by institutions to report losses

ii) Control bias – occurs when data is collected from institutions with different control systems

iii) Scale bias – occurs when data is collected from institutions with different sizes

There are many techniques suggested by various authors on how to correct inherent bias. De Fontnouvelle et al. (2003) proposed using a stochastic truncation model to correct for reporting bias where they treat each institution's loss reporting threshold as an unobserved random variable. Dahen & Dionn (2007) and Na et al. (2005) provides an elegant method to remove scale bias by assuming operational losses can be broken into two components: a component that is common for all firms in the industry and an idiosyncratic component specific to each firm. They assume idiosyncratic component depends on factors such as firm size, location, business lines etc. They estimate the influence of each factor using regression analysis. Correcting for control bias is much harder since it is difficult to obtain information about the control mechanism of the institution which data is coming from due to disclosure constraints in the external databases. Thus the modeler needs to select data using his own opinion on how relevant the data is to his company given the difference in standard risk management practice in the industry and his own company. A detail discussion on recent advances in correcting inherent bias for external data sources can be found in APRA (2007b).

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, black swan approach focuses on the LF/HS events, risk that posses greatest threat to the solvency of the company. One major drawback of the method is that it does not take into account the probability of the losses. Thus method may lead to conservative capital estimates.

5. 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. The 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. Therefore 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.

6. Discussion

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.

We look into different techniques available for super funds to measure their OpRisk by drawing techniques used by various industries to measure their OpRisk. We report that there are many methods available to measure known-known risks. Choice of the method will depend on the factors such as problem in hand, data availability and time & budget constraints. In summery 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 are 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 seems to provide best results in terms of accuracy, but however, due to time and cost involve in setting up a causal model most firms might find these models less feasible to implement. Therefore they might be useful to measure OpRisk in high risk business units rather than in a firm-wide level. On the other hand RDCA seems to provide a good trade-off between performance and time/cost. If properly set up RDCA can provide fairly forward-looking estimates of OpRisk capital charge, behavioral incentives and early warning signs to managers.

In order to asses the risk due to known-unknown OpRisk we propose to stress test 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 obtain under known-known risk and known-unknown risk.

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