Practical methods of modelling operational risk

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The final frontier for actuaries?
Agenda

1. Why model operational risk?
2. Data.
5. Some results.
6. The way forward...
Before we start ... definition of operational risk

- Basel definition now also used under SAM and Solvency II:
  
  “Operational risk is the risk of loss arising from inadequate or failed internal processes, or from personnel and systems, or from external events. Operational risk should include legal risks, and exclude risks arising from strategic decisions, as well as reputation risks. “

- Only cover operational risks to the extent that these have not been explicitly covered elsewhere in the capital

- Capital is required only for risks that impact the cashflows underlying the base balance sheet, therefore e.g. strategic risk not included
Why model operational risk

- Improve understanding of operational risk – results can be scary but revealing
- Scenario workshops and allocation of capital to business units focus the mind of operational areas on operational risk
- Models enable you to test the effectiveness of mitigation strategies – insurance and internal controls
- Data useful for measurement and monitoring, MI
- Pillar II of SAM – help you to assess whether standard formula appropriate
- Opportunity to learn some new statistical and mathematical methods...
Data

- Internal loss data
- External loss data
- Scenario based analysis
- Business environment and control factors
Internal Loss Data

- Good practice to have policies in place for collection of internal loss data
- Process must be transparent and include review and approval
- Things to consider:
  - Collection threshold
  - What to include in operational risk losses
  - Consistent recording across different departments and business units
  - Data fields required for modelling

Internal data seldomly sufficient as a result of low frequency of occurrence and short collection period

Need to adjust fitting for truncation. If truncation not consistently applied you may need a stochastic model.
External Loss Data

- Various consortium, industry-wide data schemes are available for banking industry (ORX, BBA Gold, Algo First)
- Association of British Insurers launched ORIC for insurers – at least three South African participants
- Survey conducted by Martin & Hayes (2013) shows that 86% of South African insurers would be interested in joining a consortium as subscriber and 75% as a contributor
- What can we learn from ASSA CSI committee?
  - Scaling of data to be appropriate
  - Potential bias in external data – only the large publicly known losses may be reported
Scenario Analysis

• Starting point for modelling is what happened in the past, but need to allow for changes in operating and control environment
• For some low frequency categories sufficient data will not be available for many years
• Use qualitative measures to calibrate a statistical model
Scenario Analysis

• Scenario workshops:
  • Involve senior people from relevant areas of business
  • Need to formulate questions so that correct responses are obtained from audience not trained in statistics

• “loss of $x$ occurs every $d$ years”

• Combine scenarios with historical data...

• …or use only scenarios to fit frequency and severity distributions
Methods available for modelling operational risk

Top-down approaches

Bottom-up approaches
Methods available for modelling operational risk

- **Standard formulae**
  - Basic Indicator Approach under Basel
  - Standard formula specified by Solvency II and SAM
  - Standardised Approach under Basel – standard formula that is more sensitive to mix of business

- **Advanced Modelling Approaches**
  - Internal Measurement Approach under Basel – standard formula with user-specified parameters calibrated from internal data
  - Loss Distribution Approach
  - Scorecard Approach

- **Other methods**
  - e.g. Bayesian causal networks

**Increased complexity and data requirements**
Standard formulae

Basel has hierarchy of standard formulae

- SAM standard formula based on Solvency II
- CEIOPS calibration paper explains that parameters were set by considering operational risk capital charges from insurers with operational risk models…but many of the models were not robust
QIS3 formula for operational risk

\[ SCR_{op} = \min(0.3 \times BSCR; Op) + 0.25 \times \exp_{ul} \]
\[ Op = \max(Op_{prem} \text{; } Op_{prov}) \]
\[ Op_{prem} \]
\[ = 0.04(Earn_{life} - Earn_{ul}) \]
\[ + \max \left( 0; 0.04(Earn_{life} - Earn_{ul}) \right) \]
\[ Op_{prov} \]
\[ = 0.0045 \times \max(0; TP_{life} - TP_{ul}) + 0.03 \]

Feedback from QIS2:
- Formula not risk-sensitive
- Does not take business-specific conditions into account
- Concerns with the link between operational expenses and operational risk capital raised by linked insurers
The model

• Operational risk losses similar to general insurance claims
  • there can be multiple losses per year
  • the amount of the loss is variable

• Use frequency/severity approach a.k.a. “the actuarial approach” a.k.a. the Loss Distribution Approach (LDA) as per Basel II/III

• For each operational risk category $i$:

$$L_i = \sum_{j=1}^{N_i} L_{i,j}$$

- Number of losses per period
- Homogeneous category e.g. split by event type/business line
- The amount of the $j^{th}$ loss for category $i$
The model (for each $i$)

Severity distribution for $L_{i,j}$

Frequency distribution for $N_i$

Convolution

Monte Carlo simulation

Distribution for $L_i$

- Expected loss
- $99.5^{th}$ percentile
- Unexpected loss
The severity distribution

- Fat tailed distribution required
  - Lognormal: most often used
  - Other options Weibull, Beta
- Often fit different distributions to body and tail of the distribution
- EVT used to fit distribution to tail
  - Generalised Pareto Distribution often used
- Need to blend body and tail distribution to get a valid distribution function for each category
The severity distribution

- Use exploratory data analysis to find appropriate distribution for each category
- Range of goodness-of-fit tests are available to determine whether chosen distribution is appropriate
The frequency distribution

- Discrete distribution required for the number of operational risk losses per category per period
- Bernoulli, Poisson or Negative Binomial

Ideal for low frequency events, but mean and variance the same
Underlying assumptions

- Individual losses are independent of each other
- The individual losses are independent of the number of losses per period

These assumptions have implications for the correlation structure that can be used…
Correlation

- Different categories of operational risk are not perfectly correlated … summing the capital charges may be conservative
  - E.g. low correlation between discrimination in the workplace (Employment practices and workplace safety) and External Fraud
- Does correlation between aggregate losses for different categories arise from correlation between severity distributions or frequency distributions?
Correlation

- Practical ways of allowing for correlation:
  - Ignore it and just sum the capital charges from the different categories...being conservative
  - The variance-covariance approach (used in the standard formula SCR approach)
  - Copulas
Correlation

- To calculate the total capital charge for operational risk more simulation required

- For each simulation:
  - Simulate a $u(0,1)$ variable for each of the operational risk categories using the copula function
  - Find the loss from the aggregate loss distribution for each category by applying $x_i = F^{-1}(u_i)$
  - Sum all the losses together to give the total loss for the simulation from all the different categories

- Order all the total losses from simulation from small to large
- Pick the observation corresponding to the percentile (e.g. for 10000 simulations take 9950th observation as capital)
Correlation

- Need to allocate total capital back to the categories – allocation to different business units very important as this is the level at which operational risk is controlled

- Should one allow for correlation between operational risk and other risks?
  - Basel allows no diversification benefit
  - Standard formula SCR under SAM allows no diversification
  - Will be difficult to calibrate and justify?
Some results

- Features of the data determine the modelling
- As a simple example consider:
  - Truncated data (i.e. only data above a certain threshold is collected)
  - Simulate losses over a period of 5 years a 100 times
  - Truncate simulated losses at R5000
  - Fit distributions to data using a method that allows for data truncation and a method ignoring the truncation
  - Calculate the 99.5\textsuperscript{th} percentile from the fitted distributions for each simulation

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Severity</th>
<th>Truncation point</th>
</tr>
</thead>
<tbody>
<tr>
<td>• Poisson</td>
<td>• Lognormal</td>
<td>• R5000</td>
</tr>
<tr>
<td>• $\lambda = 20$</td>
<td>• $\mu = 10$</td>
<td></td>
</tr>
</tbody>
</table>
Some results

Actual 99.5\textsuperscript{th} percentile is R1.68m

Averages:
- Allowing for truncation: R1.65m
- Not allowing for truncation: R1.44m
## Some results

- How accurate is capital based on scenarios?
- “A loss of $x$ or higher occurs once every $d$ years”
- As a simple example consider:

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Severity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Poisson</td>
<td>Lognormal</td>
</tr>
<tr>
<td>$\lambda = 4$</td>
<td>$\mu = 11$</td>
</tr>
<tr>
<td></td>
<td>$\sigma = 2$</td>
</tr>
</tbody>
</table>

- Calculate the actual values of $x$ for 1, 2, 5 and 20 year events
Some results

- Two scenarios were tested with differing levels of uncertainty around the true value of $x$

- Scenario 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%</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%</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%</td>
<td>3 708 472.08</td>
<td>6 887 162.43</td>
</tr>
</tbody>
</table>

- Scenario 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>6.25%</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%</td>
<td>4 503 144.67</td>
<td>6 092 489.84</td>
</tr>
</tbody>
</table>
Some results

- Simulate values for x for each d from the above ranges assuming a uniform distribution
- Calculate the 99.5\textsuperscript{th} percentile and compare with actual 99.5\textsuperscript{th} percentile from the distribution of R26.7 million
- Results from 1000 simulations:

<table>
<thead>
<tr>
<th></th>
<th>Scenario 1</th>
<th>Scenario 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>10 245 282</td>
<td>15 103 795</td>
</tr>
<tr>
<td>Max</td>
<td>64 988 139</td>
<td>50 888 477</td>
</tr>
<tr>
<td>Average</td>
<td>28 575 139</td>
<td>27 127 678</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>10 825 108</td>
<td>6 015 802</td>
</tr>
</tbody>
</table>
Conclusions

• Allow for all features of the data in the modelling
• Use all available data to inform scenarios as the closer to the actual values the scenario data is, the better the resulting capital calculations
• Use some form of randomisation with scenario data
The way forward...
The way forward…

• Get some loss data and then get some more
• Consider the intricacies around modelling, data and scenarios today even though modelling may only be viable many years in the future
• Get a better understanding of operational risk for insurers and how the unique features should be modelled
• Get familiar with the mathematics
• Realise that it will be a long-term journey, but have fun along the way…